

**DECISION SUPPORT MODEL IN FAILURE-BASED
COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM
FOR SMALL AND MEDIUM INDUSTRIES**

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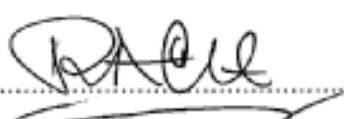
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COMPUTERIZED MAINTENANCE MANAGEMENT SYSTEM
FOR SMALL AND MEDIUM INDUSTRIES

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

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JULY 2009

I hereby declare that this thesis, entitled "Decision Support Model in Failure-based Computerized Maintenance Management System for Small and Medium Industries" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and it is not concurrently submitted in candidature of any other degree.

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Special dedication to:

My beloved mother, Hajjah Ahbida binti Rahimathulla,
my beloved wife, Azizah binti Haji Vaheed and
our cute children, Aina Jasmin and Ahmad Farhan

For all the help that they have rendered.
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ABSTRACT

Maintenance decision support system is crucial to ensure maintainability and reliability of equipments in production lines. This thesis investigates a few decision support models to aid maintenance management activities in small and medium industries. In order to improve the reliability of resources in production lines, this study introduces a conceptual framework to be used in failure-based maintenance. Maintenance strategies are identified using the Decision-Making Grid model, based on two important factors, including the machines' downtimes and their frequency of failures. The machines are categorized into three downtime criteria and frequency of failures, which are high, medium and low. This research derived a formula based on maintenance cost, to re-position the machines prior to Decision-Making Grid analysis. Subsequently, the formula on clustering analysis in the Decision-Making Grid model is improved to solve multiple-criteria problem. This research work also introduced a formula to estimate contractor's response and repair time. The estimates are used as input parameters in the Analytical Hierarchy Process model. The decisions were synthesized using models based on the contractors' technical skills such as experience in maintenance, skill to diagnose machines and ability to take prompt action during troubleshooting activities. Another important criteria considered in the Analytical Hierarchy Process is the business principles of the contractors, which includes the maintenance quality, tools, equipments and enthusiasm in problem-solving. The raw data collected through observation, interviews and surveys in the case studies to understand some risk factors in small and medium food processing industries. The risk factors are analysed with the Ishikawa Fishbone diagram to reveal delay time in machinery maintenance. The experimental studies are conducted using maintenance records in food processing industries. The Decision Making Grid model can detect the top ten worst production machines on the production lines. The Analytical Hierarchy Process model is used to rank the contractors and their best maintenance practice. This research recommends displaying the results on the production's indicator boards and implements the strategies on the production shop floor. The proposed models can be used by decision makers to identify maintenance strategies and enhance competitiveness among contractors in failure-based maintenance. The models can be programmed as decision support sub-procedures in computerized maintenance management systems.

ABSTRAK

Sistem bantuan keputusan penyelenggaraan adalah penting untuk memastikan keupayaan dan kebolehpercayaan peralatan di dalam barisan pengeluaran kilang. Tesis ini menyelidik beberapa model bantuan keputusan untuk mengurus penyelenggaraan di industri kecil dan sederhana. Kajian ini memperkenalkan sebuah kerangka untuk digunapakai di dalam penyelenggaraan berasaskan kegagalan mesin bagi meningkatkan kebolehpercayaan barisan pengeluaran. Beberapa strategi penyelenggaraan dikenalpasti menggunakan model Kekisi Penghasilan Keputusan berasaskan dua faktor penting iaitu masa dan kekerapan kerosakan mesin. Mesin dikategorikan kepada tiga kriteria mengikut masa dan kekerapan kerosakan mesin iaitu tinggi, sederhana dan rendah. Penyelidikan ini telah menerbitkan rumus berdasarkan kos penyelenggaraan mesin bagi model Kekisi Penghasilan Keputusan. Seterusnya, rumus analisa kelompok di dalam model Kekisi Penghasilan Keputusan diperbaiki bagi menyelesaikan masalah kepelbagaian kriteria. Penyelidikan ini juga memperkenalkan rumus untuk menganggar masa bertindak dan pembaikan mesin oleh para kontraktor. Segala anggaran ini akan digunakan sebagai parameter input di dalam model Proses Analitikal Hiraki. Keputusan disintesis berdasarkan kemahiran teknikal kontraktor seperti pengalaman penyelenggaraan, kemahiran menganalisa masalah dan kepantasan bertindak semasa pembaikan mesin. Kriteria lain yang dipertimbangkan di dalam model Proses Analitikal Hiraki ialah dasar perniagaan kontraktor, termasuk kualiti penyelenggaraan, kelengkapan peralatan dan semangat di dalam menyelesaikan masalah. Data mentah dikumpulkan melalui tinjauan, temubual, kaji selidik dan ujikaji di beberapa buah industri makanan kecil dan sederhana bagi memahami beberapa faktor risiko. Kesemua faktor risiko tersebut dianalisis dengan gambarajah Ishikawa bagi mengenalpasti masa langkah di dalam penyelenggaraan mesin. Model Kekisi Penghasilan Keputusan boleh digunakan bagi mengesan sepuluh mesin paling bermasalah di barisan pengeluaran. Model Analisa Proses Hiraki digunakan bagi mengenalpasti kontraktor dan strategi penyelenggaraan yang terbaik. Penyelidikan ini mencadangkan supaya hasil dipamirkan dan strategi dilaksanakan di barisan pengeluaran kilang. Kesemua model cadangan di atas boleh digunakan bagi mengenalpasti strategi penyelenggaraan dan meningkatkan tahap daya saing kontraktor di dalam aktiviti penyelenggaraan berasaskan kegagalan mesin. Kesemua model yang disebutkan di atas boleh diprogramkan sebagai sub-prosidur bantuan keputusan di dalam sistem pengurusan penyelenggaraan berkomputer.

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LIST OF ABBREVIATIONS AND SYMBOLS

ABBREVIATIONS	MEANINGS
<i>AHP</i>	Analytical Hierarchical Process
<i>AI</i>	Artificial Intelligence
<i>ANOVA</i>	Analysis of Variance
<i>ARMA</i>	Auto-Regressive Moving Average
<i>CBM</i>	Condition-based Maintenance
<i>CI</i>	Consistency Index
<i>CMMS</i>	Computerized Maintenance Management System
<i>CR</i>	Consistency Ratio
<i>DBM</i>	Detection-based maintenance
<i>DMG</i>	Decision-Making Grid
<i>DOM</i>	Design-out Maintenance
<i>DSM</i>	Decision Support Model
<i>DSS</i>	Decision Support System
<i>FAMA</i>	Federal Agricultural Marketing Authority
<i>FBM</i>	Failure-based Maintenance
<i>FMEA</i>	Failure Mode and Effects Analysis
<i>FMECA</i>	Failure Mode, Effects and Criticality Analysis
<i>FTM</i>	Fixed Time Maintenance
<i>IT</i>	Information Technology
<i>KMO</i>	Kayser-Meyer-Olkin
<i>KPI</i>	Key Performance Index
<i>MARDI</i>	Malaysian Agriculture Research and Development Institute
<i>MATLAB</i>	Mathematical Laboratory

<i>MCDM</i>	Multiple Criteria Decision-Making
<i>MDT</i>	Mean Downtime
<i>MILP</i>	Mixed Integer Linear Programming
<i>MInLP</i>	Mixed Integer non-Linear Programming
<i>MTBF</i>	Mean Time Between Failures
<i>MTTR</i>	Mean Time to Repair
<i>OTF</i>	Operate to Failure
<i>PHM</i>	Proportional Hazards Model
<i>PM</i>	Preventive Maintenance
<i>QFD</i>	Quality Function Deployment
<i>RBM</i>	Risk-based Maintenance
<i>RCM</i>	Reliability-centred Maintenance
<i>RI</i>	Random Index
<i>RPN</i>	Risk Priority Number
<i>RPR</i>	Risk Priority Rank
<i>SLU</i>	Skill Levels Upgrade
<i>SMI</i>	Small and Medium Industries
<i>SMIDEC</i>	Small and Medium Industries Development Corporation
<i>SPSS</i>	Statistical Package for the Social Sciences
<i>SQL</i>	Standard Query Language
<i>TPM</i>	Total Productive Maintenance
<i>TPQM</i>	Total Planned Quality Management
<i>TQM</i>	Total Quality Maintenance
<i>UBM</i>	Use-based Maintenance
<i>UTeM</i>	Universiti Teknikal Malaysia Melaka
<i>UTM</i>	Universiti Teknologi Malaysia
<i>VBM</i>	Vibration-based Maintenance

SYMBOLS	MEANINGS
α	Alpha
\in	Belongs to
β	Beta
R^*	Complex conjugate of R , signified by asterestics as superscript
\wedge	Conjunction
Δt	Delta t , small change applied to time, t
\hat{R}	Estimate of R , signified by the use of caret or hat
e	Exponential
\forall	For all
Γ	Gamma
$>, \geq$	Greater than, greater than or equal to
∞	Infinity
\int	Integration
λ	Lambda
Π	Multiplication
π	Pi
$<, \leq$	Smaller than, smaller than or equal to
τ	Tau
$\sum_{i=1}^n$	The summation from i equals 1 to n

LIST OF GLOSSARIES

GLOSSARIES

Bold lower-case alphabet

Bold upper-case alphabet

Italic lower-case symbols

The closed interval $[a, b]$

The closed-open interval $[a, b)$

The open interval (a, b)

The open-closed interval $(a, b]$

NOTES ON MEANING AND USAGE

Used for vectors

Used for matrices

Used for scalars

The set of a variable x signifies that $a \leq x \leq b$

The set of a variable x signifies that $a \leq x < b$

The set of a variable x signifies that $a < x < b$

The set of a variable x signifies that $a < x \leq b$

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CHAPTER 1

INTRODUCTION

1.1 Preamble

Small and Medium Industries (*SMI*) are the key contributors to economic growth in Malaysia and their background are explained in section two of this chapter. The section elaborates on how *SMI* have been established and their classifications, followed by their contribution to generating employment and income to the country. In the long run, *SMI* in Malaysia are expected to excel in line with policies and incentives introduced by the government. The main objectives of their businesses are to engage in small- and medium-scale manufacturing lines to generate profit and employment. Despite this, when compared to *SMI* in many other developed economies, such as Japan, Australia and Germany, the local players have clearly not reached their full potential. One of the factors that is lacking is technology management, *i.e.* machinery maintenance. Thus, the effect of machinery failures is presented in the next section of this chapter.

Section three gives a background on the maintenance and computerized system, followed by a background on the decision support and optimization system in section four. Development of maintenance decision support models will help to provide alternatives, strategies and solutions in maintenance activities. For instance, it

may require the re-layout of production lines, staff re-engineering, re-structure of the contractors, maintenance re-scheduling, *etc.* Section five explains the decision support system in computerized maintenance management system with the Holonic concept. It continues with a brief description of the decision-making grid and an introduction to the analytical hierarchical process.

Poor machinery maintenance management will result in capacity loss, poor product quality and customer dissatisfaction. These downturns usually occur depending on the effectiveness of the reliability of programs executed by the organization. The performance of a maintenance team in bringing up the machine is very difficult to measure accurately. This is because the outcome of a service process is inherently much more inconsistent issues in quality than the manufacturing counterparts. Furthermore, the service process is difficult and expensive to control. Section six discusses these issues in *SMI*. The section continues with statements of the problems, and research questions. Section seven gives the objectives of our studies, and section eight provides the scope of the study. Section nine provides the significance of the study, the organisation of the thesis is explained in section ten, and the conclusion is in section eleven.

1.2 Background to Small and Medium Industries

In general, small and medium food processing industries in Malaysia are initiated as a family business, owned by a single proprietor. However, as the industry expands, a partnership normally evolves, with strong support from the government (Senik, 1995). The locations of *SMI* tend to be evenly distributed, and are found in both rural and urban areas. Lately, they have even been engaged in the industrial trade zones to support large-scale industries.

According to the Small and Medium Industries Development Corporation (*SMIDEC*), small-scale companies are those that have 5 to 50 full-time employees, whilst medium-scale companies employ 51 to 150 employees (Ghani, 2004). A small-

scale company operates with capitals of less than RM250,000.00, and a medium-scale company with capitals of RM250,000.00 to RM1,000,000.00. A small-scale company's annual turnover is between RM250,000.00 and RM10,000,000.00, and a medium-scale company's annual turnover is between RM10,000,000.00 and RM25,000,000.00. Companies under those limits are considered micro-scale industries, whereas companies beyond those limits are considered large-scale industries (Shamsuddin *et al.*, 2004).

As with food processing industries, marketing is done either directly or through government, semi-government or private agencies. According to *SMIDEC*, the Malaysian government has established a good network to facilitate trading between the different food manufacturing partners in the global *halal* market, in the ninth Malaysian Plan. Malaysia is one of the moderate Islamic countries in the world with the necessary infrastructure, a well-diversified muslim's workforces, and related resources. Therefore, Malaysia is able to provide a stable Islamic hub at a relatively low cost to produce, promote, export and manage their *halal* foodstuffs, for any international or multinational *halal* food processing industries.

1.2.1 Contribution of Small and Medium Industries

The largest portion of manufacturing firms fall into *SMI* categories and the *SMI* businesses are the backbone of the large-scale industry. Therefore, *SMI* is the ultimate kernel of the economy system (Shamsuddin *et al.*, 2004). According to the Federation of Malaysian Manufacturers' Directory in 1999, *SMI* employ 60 percent of 668,174 employees in Malaysia. From an annual sales value, *SMI*'s share 64 percent of the sales in the country. Employment and sales were expected to grow rapidly until now.

In Malaysia, there is evidence that *SMI* account for about 35 percent of the country's gross domestic product (Kushairi, 2008). Ainul (2008) reported that the share in gross domestic income of *SMI* is expected to increase from 35 percent to 37

percent by 2010. This is because it is evident that many *SMI* are starting to export their products to international markets. The Malaysian government has realized the importance of *SMI* contribution and it will have to strive hard in order to achieve the country's vision by the year 2020. Reportedly, there are a few thousand *SMI* firms in Malaysia across different industry groups. However, Shamsuddin *et al.* (2004) commented that there are not many studies on maintenance management have been conducted for *SMI*.

1.2.2 Effects of the Machinery Failures

The primary functions of most machines in industries are concerned, in some way, with the need to earn revenue or to support revenue-earning activities. Poor machinery maintenance will lead to more emergency breakdowns. The breakdowns affect the production capability of physical assets by reducing output, increasing operational costs, and, thus, interfering with customer services. Machinery failures in *SMI* production lines will increase the operation cost and reduce their profit margin. There are five reasons why downtime can affect factory operations (Moubray, 1997):

- (i) Total output: where the production people have to work extra time to recover the volumes and losses. Imagine if the plant is already fully loaded;
- (ii) Quality control: where failures cause materials to deteriorate. Products which do not reach certain quality specifications have to be rejected;
- (iii) Operating costs: in addition to the direct cost, repairing the machines will increase the use of energy or it might involve switching to more expensive, alternative solutions;
- (iv) Sales: where the prices of the end products have to be increased to recover the downtime as well as the production losses; and
- (v) Customer service: frequency of machine failures shows the reputation of the factories. Poor service may cause customers to shift their business deals elsewhere.

In brief, the effects of downtime are much greater than the cost of repairing the failures. For example, if a filling machine fails in a *SMI* production line, the end products will spill over. This also results in labour safety issues as well as business losses.

1.3 Computerized Maintenance Management System

Over the past twenty years, Moubray (1997) has highlighted that maintenance has changed, perhaps more than any other management discipline. This is due to huge increases in the number and variety of machines with complex designs, which must be maintained carefully.

The evolution of maintenance can be traced throughout three generations. Since the 1930s, the first generation covers the period up to World War *II*. During this period, industries were not widely mechanized and downtimes were not considered seriously. Most of the equipment was simple, designed only for specific missions and easy to repair. The maintenance activities involved cleaning, servicing, and lubrication, and were only routine. Things changed dramatically in the second generation during World War *II*. Wartime pressures increased the demand for goods of all kinds, while the supply of industrial manpower dropped rapidly, which led to an increase in mechanization.

The 1950s has been viewed as a significant era, where the equipment became more numerous and complex in design and any failures led to a substantial impact on its operation. During this time, downtime became the most salient issue. This led to the idea that equipment failures should be prevented, and this, in turn, led to the rapid growth of maintenance control and reliability studies. The 1970s was the third generation, when the process of change in the industrial sectors increased at a tremendous rate. Most equipment was designed for multipurpose and multitasking functions, which made repair activities more sophisticated. The rapid growth of this mechanization and automation implies that more significant studies have been carried

out on maintenance reliability and availability to date. The Computerized Maintenance Management System (*CMMS*) is used as a database in which to store all basic information on maintenance activities.

Today, maintenance is going global, being faced with virtual factories and flexible manufacturing demands for a more advanced maintenance management system. The *CMMS* usage is extended from a data storage device to assisting in the supply chain management and administrative functions for effective, proactive and reactive maintenance. Advanced techniques that implement backup and standby strategies, as well as computer simulation and automatic monitoring, are widely used. Tremendous innovations in the computer networking and information communication technology arena make these achievable in the challenging world. A maintenance crew is expected to be able to repair the equipment remotely, using factory automation computer-aided tools such as *teamstation*, *LANDesk*, *remote power management*, *PC Anywhere*, and other remote maintenance control systems, in order to sustain itself in the global market.

The next generation of machines is designed to learn from the previous failure records in the *CMMS*. Therefore, in the next failure attempts, the machines are equipped with some self-maintenance capabilities to recover from those failures by themselves (Labib, 2006).

Generally, the *CMMS* is able to provide certain advantages, as follows (Williams and Sawyer, 2006):

- (i) Improved data integrity: data is more accurate, consistent and up to date;
- (ii) Increased security: different passwords can be used to share specific information between selected users;
- (iii) Data maintenance: easy to edit data in their field at anytime; and
- (iv) Data redundancy: backup strategies to ensure the availability of data in case of any failures and disasters of the primary data sources.

1.4 Decision Support System and Optimization

A Decision Support System (*DSS*) is a computer-based information system that provides a flexible tool for analysis, and helps managers to make decisions and forecasts for the future. The cost of maintenance itself is still rising along with *CMMS*, in absolute terms and as a proportion of total expenditure. In some industries, one of the highest spending elements in production is the operating cost. As far as information technology is concerned in the area of maintenance, achieving a low production cost involves not only the study of techniques and the application of *CMMS*, but also a decision regarding which items are worth prioritizing for the respective functional groups in the organization. *DSS* gathers and presents data from a wide range of sources in a way that can be interpreted by humans. Moubray (1997) discussed some new developments in maintenance, as follows:

- (i) Designing equipment with a much greater emphasis on reliability, such as introducing backup and standby strategies;
- (ii) Teamwork and flexibility to optimize the maintenance team's performance;
- (iii) Expert systems, such as automatic condition monitoring and remote maintenance control; and
- (iv) Decision support tools, such as regression analysis, cluster analysis, decision-making grid, failure modes, and effects analysis, *etc.*

Since then, more thorough analyses have been obtained, such as failure complexity studies, failure root cause analysis, response time analysis, repair time analysis, and delay time analysis. Previous studies have not yet provided enough evidence on the usage of *DSS* in *CMMS* for *SMI*. In fact, there is a growing need for *SMI* to be equipped with *CMMS* complete with the maintenance management practice, including (Lindley *et al.*, 2002):

- (i) Corrective maintenance, which includes such improvements as minor changes in design, and the substitution of more suitable components or improved materials of construction to eliminate a problem;

- (ii) Predictive maintenance is a relatively new term, which has not come into general use. It is logical to consider the use of sensing, measuring, or monitoring devices to determine any significant changes. Periodic measurement or monitoring using sensors can identify conditions that require correction before a major problem develops;
- (iii) Repair maintenance is simply doing maintenance work as the need develops. It can be the most logical approach to maintain non-critical equipment or parts of a production system; and
- (iii) Preventive maintenance, which is undertaken before the need develops, to minimize the possibility of unanticipated production interruptions or major breakdowns. It is always practiced when:
 - (a) Corrective maintenance cannot be justified;
 - (b) Predictive maintenance cannot be applied; and
 - (c) Repair maintenance effects cannot be tolerated.

Features of *DSS* are given as follows (Williams and Sawyer, 2006):

- (i) Inputs and outputs;
- (ii) Assist tactical-level managers in making tactical decisions; and
- (iii) Produce analytical models, such as mathematical representation of a real system.

A quantitative approach in the *DSS* model allows maintenance managers to play a simulation *what-if* game to reach decisions. They can simulate an aspect of the organization's environment in order to decide how to react to a change in the conditions affecting it. By changing the hypothetical inputs to the maximum and minimum levels, the managers can see how the model's outputs are affected. There are four aspects to maintenance optimization models, as follows (Amik and Deshmukh, 2006):

- (i) Description of a technical system, its function and importance;
- (ii) Modelling of the deterioration of the system in time and possible consequences for this system;

- (iii) Description of the available information about the system and actions open to management; and
- (iv) Objective function and an optimization technique, which helps in finding the best practice.

1.5 *CMMS to DSS*

Planning and maintenance scheduling is important to ensure that all the resources are fully utilized on the production floor and are managed properly. This always involves a lot of managerial work to update the status of the machines and maintenance records. Also involved is the calculation of the machines' availability, reliability and costing. *CMMS* can save clerical work by providing faster information on the availability of materials, average cost, downtime, contractors' activities, *etc.* *CMMS* can increase effectiveness in planning, scheduling and cost tracking as much as 50 percent (Lindley *et al.*, 2002). The decision support analysis includes mining the data in *CMMS* using two popular problem-solving procedures, as follows:

- (i) Regression analysis: get a particular set of numerical data. Then develop a mathematical formula that fits the data; and
- (ii) Classification analysis: a statistical pattern recognition process that is applied to datasets with more than just numerical data.

DSS should be able to help maintenance management with non-routine decision-making tasks. The inputs consist of summarized reports, processed transition data, and other internal data. Figure 1.1 shows the steps taken to explore decisions from the *CMMS* database.

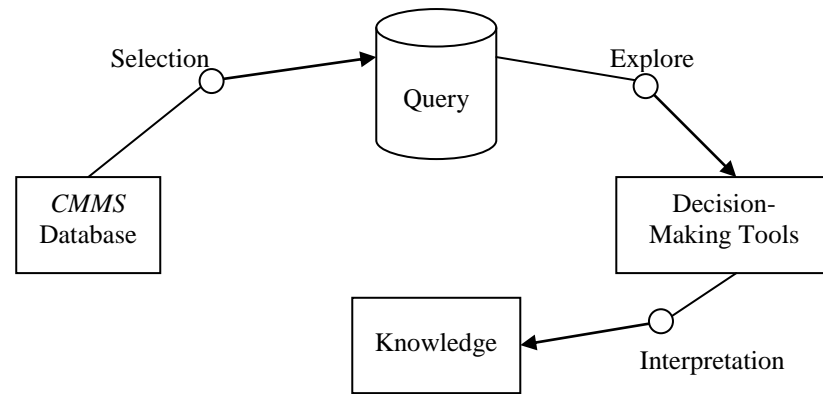


Figure 1.1: Knowledge Discovery Steps in Maintenance System

Effective *CMMS* should capture as much about maintenance work as raw data. Then, it supplies good information for decision-making, as shown in Figure 1.2 (Peters, 2006).

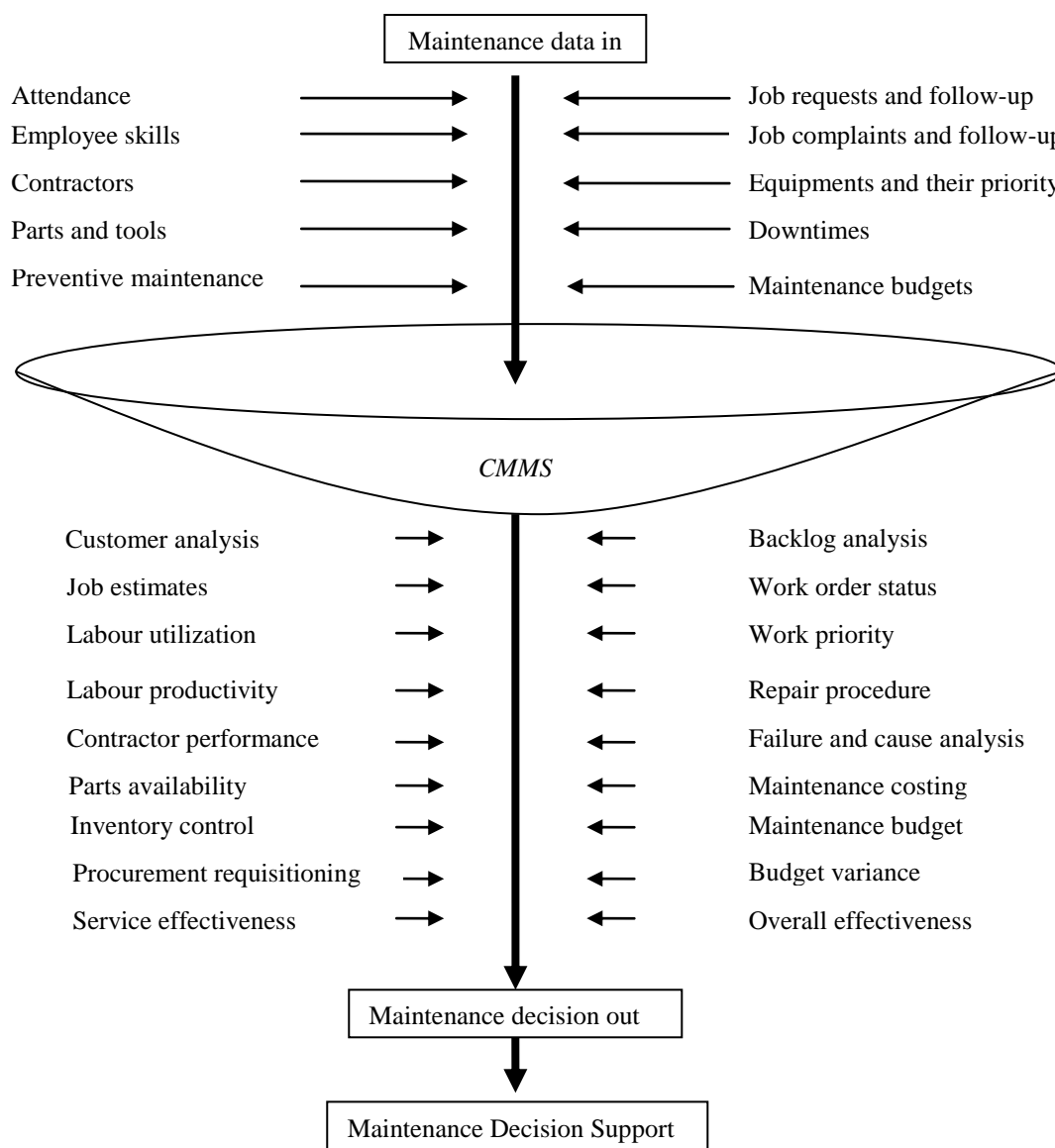


Figure 1.2: Decision Support *CMMS* (Peters, 2006)

A good *CMMS* should have some data mining capabilities, and be able to generate queries from the database, perform the calculation, and provide decisions such as:

- (i) Which machines should go for failure-based maintenance, fixed time maintenance, design-out maintenance, condition-based maintenance, preventive maintenance, *etc.*;
- (ii) When the next maintenance is due for every machine;
- (iii) Which contractor should be called to perform the maintenance work;
- (iv) Estimates of man-hours required;

- (v) Description of the tasks involved and how much time is required;
- (vi) Lists of all required replacement parts and their locations;
- (vii) Forecast on the spare parts, tools and their costs;
- (viii) Re-order level of the machine parts and other accessories; and
- (ix) An estimate of the maintenance priorities and their impact.

The most prominent objective of the various techniques in maintenance *DSS* is to supply vital data and evidence, to derive better strategies to minimize machine downtime and maintenance cost.

1.5.1 Holonic System

The Holonic concept is based on a theory developed by Koestler (1989). He defined the word *holon* as a combination of the Greek word *holos*, which means *whole*, and *on* suggesting a particle or part. The complex adaptive systems will evolve from simple systems much more rapidly if there are stable intermediate forms than if there are not. Whereas, the resulting complex system in the former case being hierarchical.

Koestler (1989) analysed hierarchy and stable intermediate forms in living organisms and social organizations. Then, he noticed that although it is easy to identify *sub-wholes* or *parts*, *wholes* and *parts* in an absolute sense do not exist anywhere. This made Koestler (1989) propose the word *holon* to describe the hybrid nature of *sub-wholes* or *parts* in real-life systems. *Holons* are simultaneously self-contained *wholes* with respect to their subordinated parts, and are dependent parts when regarded from the inverse direction. The *sub-wholes* or *holons* are autonomous, self-reliant units, which have a degree of independence and handle contingencies without asking higher authorities for instructions.

Simultaneously, *holons* are subject to control from higher authorities. The first property provided by Christensen (1994) ensures that the *holons* are stable forms that

can survive disturbances. The latter property signifies that they are intermediate forms, which provide the proper functionality for the bigger *whole*. Holonic control architecture can be used in *SMI* to comply with the concept of hierarchy in distributed systems. In order to have an efficient function in the complex system, every *holon* has to behave according to fixed rules and flexible strategies. The fixed rules form a pattern of rules governing behaviour, which lend stability and cohesion between *holons* in the group (complex system), while flexible strategies allow the *holon* to be autonomous in a framework of fixed rules. These flexible strategies enable the *holon* to determine how it operates and, particularly, how it interacts with other *holons* in that environment (Bongaerts *et al.*, 2000).

In terms of maintenance concerns in *SMI*, holonic systems can be used to answer questions like “Which machine should be improved and how?”, “What kind of maintenance strategies are to be used for this machine?”, and “How can this machine be operated more efficiently?”. Then, it is better to simplify the study by dividing the problems into sub-criteria or parts. After that, a systematic analysis with the *DMG* model is able to identify the worst production machines and determine important maintenance strategies. Consequently, the *AHP* model has to be used to estimate all available alternatives for more efficient decision-making. As a result, by using the proposed models, maintenance managers have the flexibility to implement the strategies with consideration of other industrial constraints.

1.5.2 Decision-Making Grid

The maintenance Decision-Making Grid (*DMG*), introduced by Labib (1998b), acts as a map where the performances of the worst machines are placed based on multiple criterions, *i.e.* the frequency of failures and downtime. The results provide guidelines for the action, which will lead to the movement of machines towards an improvement of the maintenance strategies with respect to multiple criterions. Labib (2004) defined the main input from the failures for *DMG* analysis as follows:

- (i) The response time;
- (ii) The diagnostic time;
- (iii) The repair time; and
- (iv) Frequency of failures.

Based on the input, machines are mapped into a two-dimensional matrix and appropriate maintenance strategies will then be implemented, such as total productive maintenance, reliability-centred maintenance, design-out maintenance, condition-based maintenance, fixed-time maintenance, *etc.* Detailed discussion on this model is given in the following chapters.

1.5.3 Analytical Hierarchical Process

The Analytical Hierarchy Process (*AHP*) is designed to solve complex decision-making problems when there are multiple objectives or criteria to be fulfilled. This approach has been introduced by Saaty (1980) and requires the decision-makers to provide judgments about the relative importance of each criterion. The first step in the *AHP* is the decomposition of the problem as a decision hierarchy. The next step is to establish priorities among the elements in the hierarchy by making pairwise comparisons of the criteria and alternatives, using linear algebra calculations. In this study, the *eigen* values and *eigen* vectors calculation is used in the matrices form. More discussion on this model is given in the following chapters.

1.6 Maintenance Issues in Small and Medium Industries

Shamsuddin *et al.* (2004) conducted a survey to study maintenance issues faced by *SMI* in Malaysia. They have listed issues related to equipment maintenance, as follows:

- (i) Lack of human resources, both in terms of number and skill or expertise;
- (ii) Emphasis on short-term gains and lack of long-term plans;
- (iii) Lack of state-of-the-art modern technology;
- (iv) Lack of understanding about the role of technology;
- (v) Insufficient funding for machinery investment;
- (vi) Lack of time to think, and re-engineering is expensive;
- (vii) Operators have poor technical knowledge about the machine they are operating;
- (viii) Poor participation from non-manufacturing units such as administration, marketing, and purchasing, *i.e.* looking at the system from the point of sub-optimization, which is contrary to Total Productive Maintenance or Total Quality Maintenance practices;
- (ix) Overall low level equipment effectiveness evaluation, especially on availability, performance rates, and quality rates; and
- (x) Slow response of the contractors on maintenance work.

Saleh and Ndubisi (2006) highlighted that *SMI* in Malaysia lack a comprehensive framework to be used in solving critical issues. Later, Kittipong (2008) conducted more comprehensive studies on technology relationships in *SMI*. He conducted the surveys and identified 20 factors of technology relationship and innovations. He conducted hypotheses and concluded that technology expertise is the first priority for *SMI* success in the area of manufacturing. *SMI* should start to look at the technology escalation procedure and manage the contractors efficiently. He has suggested a further research direction for factorial and decisional analyses using longitudinal data in his thesis.

The conjunction of these issues motivates us to visit small and medium food processing industries to understand more about their Failure-Based Maintenance (*FBM*) practice and contractor performance. In particular, some maintenance operations and issues are observed as follows:

- (i) The industries start with small capitals, and with manual and semi-automatic machines. Hence, they are not able to upgrade all the

machines in the production lines as a whole;

- (ii) Machines operate with their own specific functions in serial lines. Following this, the machines contribute to their dedicated mission in the production lines. Therefore, any failure is able to jeopardize the entire production system;
- (iii) The machines are expected to operate for at least ten hours per day, six days a week, to support the production demands;
- (iv) They just follow basic maintenance guidelines provided by the machine's suppliers. They outsource most of the *FBM* jobs to contractors. In doing so, they may over or under-maintain certain machines on the production floor; and
- (v) Every machine may have a different frequency of failures. Once failed, it has different downtimes, which include response time of the contractors and repairing time.

In addition, Junaidah (2007) reported that they are lacking appropriate decision-making capabilities in *CMMS*. They do not have a good system to evaluate the overall effectiveness of equipment, contractors' performance and their business's principles.

1.6.1 Statement of the Problems

Through the evaluation of the above maintenance dilemma in *SMI*, which is associated with maintenance decision support, statements of the problems are given as follows:

- (i) What are the important models to include in the *FBM* framework to aid maintenance decision and contractors' selection as an adoption of technology management in *SMI*? and
- (ii) How can the current available maintenance strategies be re-evaluated and embedded as a decision support module in *CMMS*?

1.6.2 Research Questions

The impact of these problems and issues has led us to extend similar work in *DMG* and *AHP* models, and to answer some research questions that arose, as follows:

- (i) How can the current maintenance practice in *SMI* be classified and modelled into a decision-making framework?
- (ii) What is the extension of *DMG* to adopt *SMI* operation?
- (iii) What kind of maintenance improvement strategies can be implemented to the machines on the *SMI* production floor?
- (iv) How can *AHP* be adopted into contractor selection for maintenance work? and
- (v) How can the best contractor be benchmarked and selected at the right time to conduct appropriate maintenance?

As mentioned, *DMG* give flexibilities in identifying maintenance strategies, whilst the *AHP* model is proposed to overcome the contractor selection problem based on the given criteria, objectives and alternatives. The ultimate aim is to derive some generalized maintenance decision support modules in *CMMS* for small and medium food processing industries. Many issues and constraints have been raised in this research work and are highlighted in the following chapters.

1.7 Objectives of the Study

This study attempts to address the following matters:

- (i) To propose a decision-making framework in *FBM* for *SMI*. Then, to suggest appropriate maintenance management strategies on the production shop floor;

- (ii) To improve mathematical calculations in the *DMG* model introduced by Labib (1998b) and Fernandez *et al.* (2003), which are able to cluster parameters for multiple criterion decision analysis;
- (iii) To formulate a machine re-positioning equation for *DMG* analysis based on maintenance cost; and
- (iv) To benchmark contractors in *FBM* jobs in *SMI*, based on the given goals, criteria, sub-criteria, alternatives and constraints using *AHP*.

1.8 Scope of the Study

These are the scope and assumptions made in the proposed study:

- (i) The downtime interval is finite;
- (ii) Focus of the study is on *FBM* upon repair. Assumptions are made that the organization has established its proactive and preventive maintenance structure;
- (iii) Failure behaviours are almost similar, and their responding and repairing time can be divided into several discrete time periods;
- (iv) The repair machine is as good as new initially and cannot fail until it begins functioning;
- (v) Each repaired unit works as good as new;
- (vi) Machine criticalities are almost equal in order to reduce model complexities;
- (vii) Model judgement is solely based upon data, and expert judgement is relaxed, due to model simplification;
- (viii) The framework of the study will be based on *DMG* and *AHP* architecture; and
- (ix) The domain of the study will focus on small and medium food processing industries.

1.9 Significance of the Study

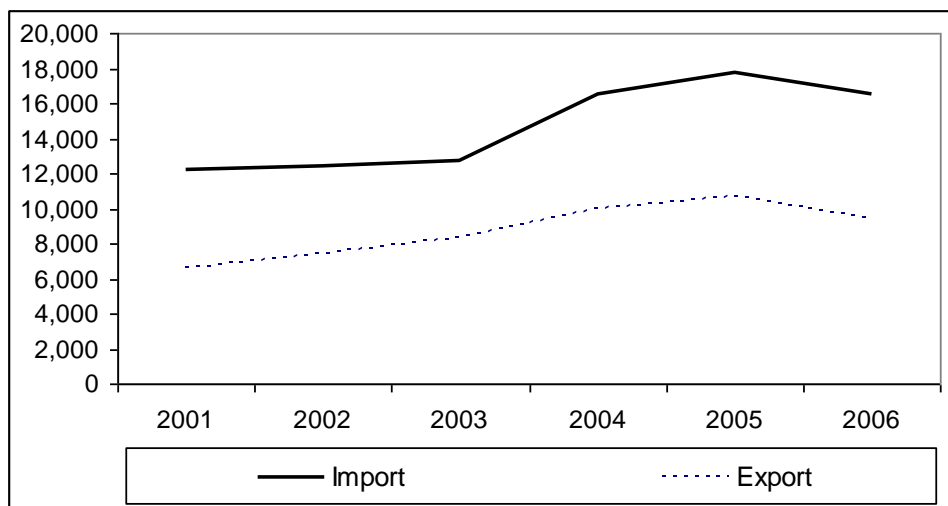
In the ninth Malaysian Plan, the Economic Planning Unit from the Prime Minister's Department has set its mission to identify and produce new resources in agro-based industries, manufacturing and services (Yassin, 2006). Ghani (2004) conducted the survey and estimated that there are 30,000 *SMI* in Malaysia, where 9,000 of them are food processing related factories, which should be able to complete the mission. Table 1.1 shows the import and export figures of foodstuffs in Malaysia from 2001 to 2006 (Department of Statistics, Malaysia).

Table 1.1: The Imports and Exports of Foodstuffs

Year	RM Million	
	Import	Export
2001	12,240	6,513
2002	12,407	7,407
2003	12,687	8,348
2004	16,554	9,930
2005	17,793	10,647
2006	16,473	9,315

(Source: Department of Statistics, Malaysia)

Figure 1.3 shows the import and export relations in a graphical format. The export of foodstuffs in Malaysia has steadily increased from 2001 to 2005. On the other hand, the import of foodstuffs gradually increased from 2001, but experienced tremendous growth after 2003. Then, the gap between imports and exports began to expand more and more over the years. The Malaysian Federal Agricultural Marketing Authority (*FAMA*) is putting tremendous effort into marketing strategies to raise the export trend of foodstuffs and bring the import trend down. In brief, they are trying to reduce the gap between imports and exports.



(Source: Department of Statistics, Malaysia)

Figure 1.3: The Imports and Exports of Foodstuffs (*RM* Million)

Malaysia has conducted the World *Halal* Forum as a yearly program, to create a good networking platform to facilitate trading between different players in the global *halal* market. There are ample opportunities for *halal* food processing companies in Malaysia to penetrate the world market especially middle east countries. However, Ghani (2004) has identified some constraints for the *SMI* to grasp these opportunities, as follows:

- (i) Usage of low-level technology and poor machinery maintenance management;
- (ii) Financial constraints to purchase and maintain sophisticated machinery on their production floors;
- (iii) Insufficient supply of good quality raw materials;
- (iv) Competitive market, as many of them are processing much the same types of products; and
- (v) Most of the development research is undertaken by research centres, such as the Food Technology Research Centre, the Malaysian Agricultural Research and Development Institute (*MARDI*), and universities, *etc.*, instead of the factories themselves. Therefore, it is a challenge to justify and deploy new techniques, and results in their production system.

Government and non-government organizations such as Malaysian Industrial Development Finance Berhad, Malaysian Development and Infrastructure Bank Berhad, SME Bank, Global Innovation Centre Sdn. Bhd., are trying their best to solve the problem described in item (ii) above, by providing the incentives and encouragement for food processing industries to play a bigger role in economic development, and to cater for more export markets (Bernama, 2009). Moreover, former Prime Minister Datuk Seri Abdullah Ahmad Badawi has announced a RM3.7 billion allocation in 2008 to implement 190 development programs in *SMI*. In addition, *SMI* are being encouraged to apply available RM51 billion funds from other financial institutions (Ainul and Asli, 2007).

Subsequently, other government agencies, such as *MARDI*, *FAMA*, *SMIDEC* are putting vigorous efforts into solving the *SMI*'s constraints for items (iii) and (iv) above with their Industrial Master Plan objectives, as follows:

- (a) To develop a modern food processing industry, meeting Malaysia's food needs in conformity with modern hygiene standards;
- (b) To establish export quality as well as import substituting products; and
- (c) To develop industries which utilize more local raw materials rather than imported ones.

There is some collaborative work between *SMI*, the Ministry of Higher Education, and the Ministry of Science, Technology and Innovation to solve item (v) above (Rosmiza, 2009).

As mentioned, there are many solutions aggressively being driven to solve the above constraints, particularly items (ii), (iii), (iv) and (v). At the moment, there are still insufficient discussions on the salient constraints in item (i). This is supported by Saleh and Ndubisi (2006), who claimed that technical assistance and advice on technology is still being utilized in *SMI*. In addition, Ramon (2009) reported that there is a growing need to conduct research on technology management in *SMI*. It includes a study on the efficient operations and technological management in *SMI*. Kittipong (2008) gave evidence of there being less understanding among people about the underlying factors influencing the adoption of technology management in

SMI. He conducted the survey in *SMI* and discovered that the technological expertise factors should be given serious attention.

This fortifies more study on outsourcing management, artificial intelligence and business solutions to aid the decision-making process for *SMI* to compete in the global market. Our study primarily focuses on improving the *SMI*'s *FBM* management. The findings obtained from this study will lead to a reduction in equipment breakdowns on the *SMI* production floors.

Above all, we provide salient contributions to the domain of knowledge in *FBM*, as follows:

- (i) Extend *DMG* model introduced by Labib (2004). We improve the formulas for clustering analyses in *DMG* model to solve the problems of multiple-criteria boundaries;
- (ii) Construct costing procedures and formulas to re-position the machines prior to *DMG* analysis; and
- (iii) Develop responding and repairing time formulas to benchmark maintenance contractors for *FBM* job using the *AHP* model.

1.10 Organization of the Thesis

This thesis contains seven chapters of presentations on the failure-based decision support maintenance model for small and medium food processing industries. The thesis begins with an introductory chapter that is motivational, paving the way for the rest of the thesis. This chapter describes the background and how downtime can effect *SMI* operation. It continues with an introduction to *CMMS*, *DSS*, *DMG* and *AHP* models, and then the issues, problem statements, research questions, objectives, scope, and their significance are discussed.

Chapter 2 discusses a review of the maintenance studies. The chapter begins with some important maintenance issues in *SMI*, and some maintenance management policies are presented. Then, investigations of the literature on information systems and maintenance techniques are described. It is noted that the scope of the literature review mainly focuses on decision-making aspects in *FBM*. Thus, theories and applications on these issues, and their relation to optimization models, are discussed. The chapter ends with several investigations on the possible extensions in similar work.

Chapter 3 explains the research methodologies in this study. The chapter identifies problems and proposes a framework, with some extensions from the literature study reviewed in Chapter 2. Next, data collection methods and investigations on maintenance work are given. Then, statistical analyses are used to calculate the central tendency values and variability of the parameters. The chapter ends with the initial development of *DMG* and *AHP*.

The processes of model fitting and testing using a raw dataset are demonstrated in Chapter 4. The *DMG* model is extended by integrating it with the clustering analysis to solve the problem of multiple criteria boundaries. Multiple criteria decision-making is re-evaluated and a comparison with the improved *DMG* model is demonstrated with case studies. An evaluation of the model is carried out using the quantitative method, and the empirical results are provided.

In Chapter 5, the model developed in Chapter 4 is enhanced with a costing parameter. Using all three parameters, *i.e.* cost, frequency of failures, and downtime, the decision support model is improved. How to prioritize the machines for *DMG* analysis is shown using quantitative measures. Then, a dataset is fitted to the proposed model and tested with the case studies.

Chapter 6 explores human capital utilization in maintenance by evaluating contractors for *FBM* jobs. Data is collected from interviews, surveys and experiments, and some approximations of the alternatives are given using the *AHP* model. Here, qualitative and quantitative methods are used. The qualitative method is used to quantify certain prominent parameters before they are fitted into the hierarchical

structure. Several significant statistical tests are also conducted to ensure that the parameters are suitable for factorial analysis.

The last part of the thesis, Chapter 7, summarizes our research work. It presents the proposed models and their contribution to this study. Finally, the chapter concludes with implications and directions for future research work in maintenance area.

1.11 Conclusion

Companies are organized into networks of manufacturing equipment to produce the finished goods to customers. Development of the maintenance decision support model in manufacturing will help to provide alternatives, strategies and solutions on crucial maintenance activities. The goal of the proposed model development is to deliver the correct maintenance strategies to the right machine at the right time. This research studies the idea of developing the maintenance management model for *SMI* with the aim of reducing the maintenance cost and time. The following chapter continues with a discussion on maintenance management literature.

CHAPTER 2

REVIEW OF THE LITERATURE

2.1 Introduction

The previous chapter gave an introduction to *SMI*, their contributions and machinery maintenance issues. As mentioned, a decision support model is required to manage technology and machines on the production floor. This chapter contains a review of the literature on the maintenance management system. The review is divided into eight sections, according to the literature on maintenance issues. The second section introduces some important maintenance issues in small and medium industries. The third section provides a general maintenance overview. Section four presents some policies in maintenance. The fifth section explains the information system, and is followed by maintenance techniques in section six. Section seven discusses optimization models in maintenance and, finally, the review is summed up with the conclusion.

2.2 Maintenance of the Machinery in *SMI*

In Malaysia, small and medium industries (*SMI*) account for about 35 percent of the country's gross domestic products. Ghani (2004) discovered that 40 to 50 percent of Malaysian requirements for processed food are being met by small-scale food industries (Ghani, 2004). Kushairi (2008) conducted a study and listed a number of factors that were lacking in Malaysian *SMI*. He managed to compare local *SMI* with those in developed economies, such as Japan, Australia and Germany. Then, he concluded that Malaysian *SMI* have still not reached their full potential and they really have to improve in some aspects, as follows:

- (i) Technological capabilities;
- (ii) Market access;
- (iii) Financial; and
- (iv) Human resource development.

In *SMI*, Ghani (2004) identified that machines always used over many years and Senik (1995) reported that there is poor maintenance has been practiced. There are insufficient efforts to mechanize, modernize and improve the efficiency of the machinery maintenance and operations. A related argument was also given by Shamsuddin *et al.* (2004), who reported that the implementation of total productive maintenance or preventive maintenance in *SMI* is still low. They proposed certain maintenance policies in *SMI*, such as total productive maintenance and total quality management implementation.

2.3 General Overview of Maintenance Management

It has been a long journey for the evolution of maintenance management models and techniques from 1940 until now. Maintenance is a wide area, and involves planning, coordinating, controlling, supervising and managing activities in

order to achieve the organization's purposes and goals. Palmer (1999) defines maintenance management as control that must be taken to keep the equipment in its working state, by preserving it from any failures. The goals of the maintenance study are to reduce downtime and cost, while improving the adequacy and quality of service to maximize the availability of equipment in an operative state. There are many literatures available from various researchers and practitioners in the field of maintenance management.

Amik and Deshmukh (2006) have presented various approaches for measuring and managing maintenance activities, where they have analysed 142 related papers. Based on the review, Amik and Deshmukh (2006) suggested some important directions for future research in the maintenance field and started a discussion about general policies in maintenance. According to them, development of the first maintenance management information system in the 1980s was due to the full recognition of maintenance as an important business function. In order to develop a good decision support model, a computerized information system design had to be revised to become a tool or enabler in maintenance management. Next, Amik and Deshmukh (2006) reviewed various techniques and their applications under the broad area of maintenance. According to them, there is still limited work directed towards developing an operational decision support system and utilizing a suitable optimization model in the area of maintenance.

After thorough investigation of the research papers, the literature in this study is organized to support the recent maintenance theory development, as shown in Figure 2.1.

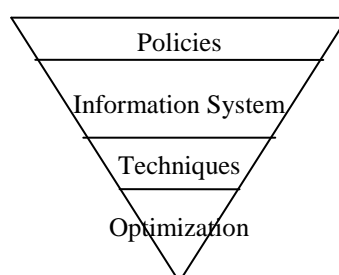
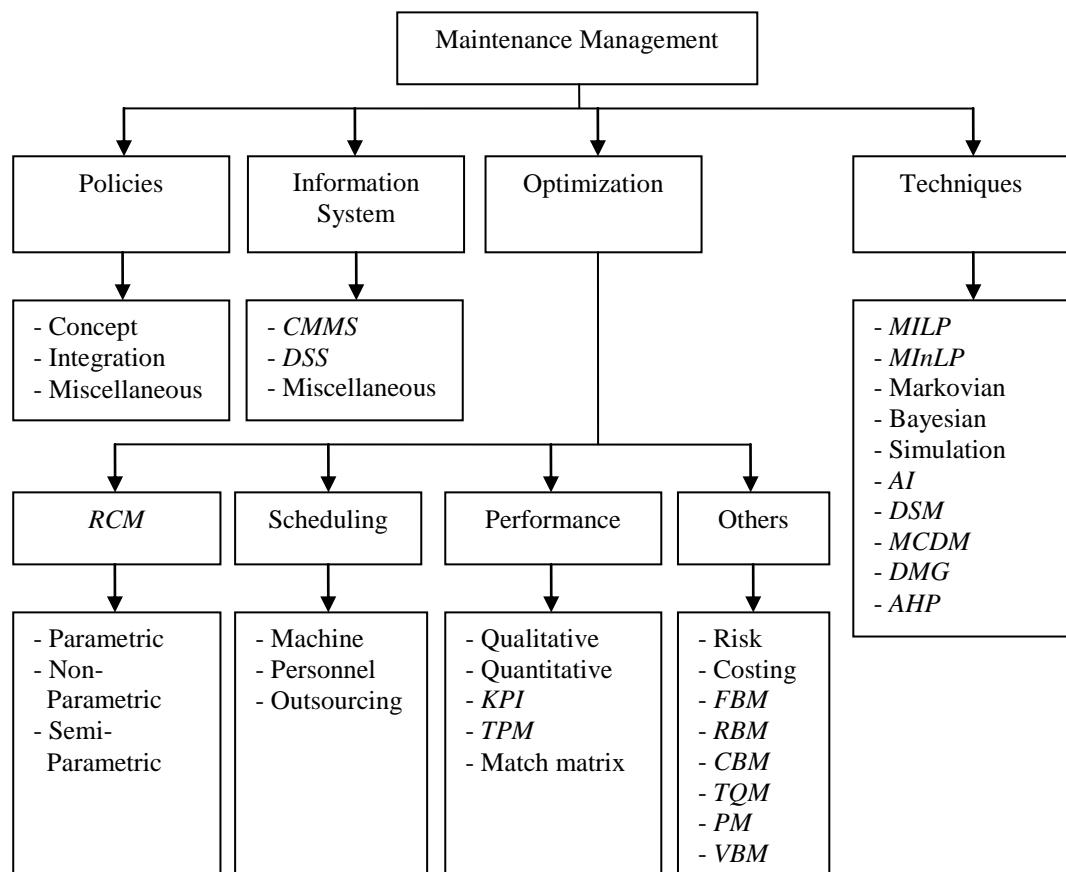


Figure 2.1: Classification of Maintenance Studies

We focus on maintenance optimization, which integrates both qualitative and quantitative techniques. Here, investigations are conducted into recent applications of the techniques in optimization to aid maintenance decision-making, especially in failure-based maintenance. Also, we provide a discussion on recent developments in maintenance optimization, to obtain the maximum production output with the minimum cost.

In this study, maintenance literature is narrowed down into four main-classes, sub-classes and sub-divisions, as shown in Figure 2.2.



Abbreviation represent: *CMMS*: Computerized Maintenance Management System; *DSS*: Decision Support System; *RCM*: Reliability-centred Maintenance; *KPI*: Key Performance Index; *TPM*: Total Productive Maintenance; *FBM*: Failure-based Maintenance; *RBM*: Risk-based Maintenance; *CBM*: Condition-based Maintenance; *TQM*: Total Quality Maintenance; *PM*: Preventive Maintenance; *VBM*: Vibration-based Maintenance; *MILP*: Mixed Integer Linear Programming; *MInLP*: Mixed Integer non-Linear Programming; *AI*: Artificial Intelligence; *DSM*: Decision Support Model; *MCDM*: Multiple Criteria Decision-Making; *DMG*: Decision-Making Grid; and *AHP*: Analytical Hierarchical Process.

Figure 2.2: Sub-division Tree of Maintenance Management

Some observations of the study in each of the above four main-classes in maintenance management and their fractions are presented in detail as follows.

2.4 Maintenance Policies

Guy and Steve (1999) reviewed the general terms of maintenance. They studied maintenance development and the reason behind it changing from time to time. After that, they focused on the enhancement and evolution of information systems in maintenance. Some important findings on enhancement of the development of information systems in maintenance are given, as they have discovered that new strategic development in maintenance is due to information system application and development.

Lam and Lin (2004) integrated some replacement policies into corrective maintenance. Corrective or Failure-based Maintenance (*FBM*) is unscheduled maintenance or repair to return the machine to a defined state. There are no interventions until a failure has occurred. Lewis (1999) addressed corrective maintenance as reactive maintenance, where any emergency breakdown will lead to a bigger impact on the operation. Since the failures are unplanned, they might result in a big loss to the organization in terms of cost and time. Therefore, a better maintenance concept must be introduced to prevent this unplanned downtime and reduce the cost of the failure. The breakdown maintenance concept is still applied to equipment that is not mission critical and where the downtime would not affect the main operation of the organization, such as light bulbs and consumable parts. Lam and Lin (2004) have introduced some numerical methods and designed optimal replacement policies in *FBM*.

According to Palmer (1999), if the plant spends a lot of time on breakdown maintenance, then it does not spend enough time on preventive maintenance. Thus, predictive maintenance is introduced to resolve deficiencies with scheduled downtime. Predictive maintenance involves monitoring certain conditions or

variables associated with the equipment (Bentley, 1993). The simplest method of condition-based monitoring involves the four human senses of sight, sound, touch and smell to predict a failure. Repairing activities take place when the condition shows that a failure may be imminent.

Unlike the Condition-based Maintenance (*CBM*) policy, in predictive maintenance the acquired controlled parameters data are analyzed to find a possible temporal trend. This makes it possible to predict when the controlled quantity value will reach or exceed the threshold values. The maintenance staffs will then be able to plan when, depending on the operating conditions, the component substitution or revision is really unavoidable. The following main activities can help to avoid machine breakdown (Bentley, 1993):

- (i) Fault detection,
- (ii) Fault isolation,
- (iii) Fault elimination, and
- (iv) Verification.

The same was demonstrated by Geert and Liliane (2004), who distinguished five basic maintenance policies in corrective and preventive maintenance. Preventive maintenance is carried out using a planned, periodic and specific schedule to keep a machine in a stated working condition, throughout the process of checking and reconditioning. Preventive maintenance is defined as the pre-breakdown model performed on equipment to either eliminate or reduce the emergency failures within pre-determined economic limits (Lewis, 1999). The model has been introduced to enhance reliability and confidence of the machine in advance. This maintenance is categorized as proactive maintenance. The service is repeated at a pre-determined frequency to avoid any unplanned breakdown of the machine. Bentley (1993) divides the preventive maintenance (*PM*) model into *CBM* with two main categories, as follows:

- (i) Monitored *PM*, which involves monitoring when the machine is in operation. Triggers on any potential failure will be detected. Repair activities are to be conducted before any unplanned breakdown; and

- (ii) Scheduled maintenance, where the service is being conducted on the same machine at specific counter or time intervals. The maintenance crew always follows the standard checklist to conduct *PM* activities, which involves scheduled replacement of parts, service, alignment, greasing, lubrication, confidence testing, *etc.*

Geert and Liliane (2004) distinguished five basic policies in maintenance, as follows:

- (i) Failure-based Maintenance (*FBM*);
- (ii) Use-based Maintenance (*UBM*);
- (iii) Condition-based Maintenance (*CBM*);
- (iv) Detection-based Maintenance (*DBM*); and
- (v) Design-out Maintenance (*DOM*).

They have suggested seven steps to follow in a modular framework on maintenance policies, before building any maintenance policies, as follows:

- (i) Identification of the objectives and resources,
- (ii) Selection of the most important maintenance systems,
- (iii) Identification of the most critical machines and their components,
- (iv) Maintenance policy selection,
- (v) Optimization of the maintenance policy parameters,
- (vi) Implementation and evaluation, and
- (vii) Feedback.

Later, Geert and Liliane (2007) discovered more findings. They have designed concrete policies and developed a framework to set up an industrial management centre. There is a group of people in the centre to control all maintenance work and escalate the work to the respective site. Their model can be used to develop a customized maintenance concept that is suitable for multinational companies.

Since centralized maintenance control in a centre requires more people, Dhillon and Liu (2006) presented the impact of human errors on maintenance. They

conducted a literature survey of human errors in maintenance and their impact on the manufacturing plant. They reported that human errors will reduce production profit. Imad (2007) highlighted the role of maintenance as a profit-generating functionality, by introducing a maintenance quality concept in the manufacturing system. He has intimated the relationship between a manufacturing system's capacity and the total manufacturing costs per unit of quality item, in order to describe and illustrate how maintenance generates profit to the company. Finally, Imad (2007) proved that maintenance is not a cost centre, but a profit-generating centre in the manufacturing sectors.

Attempting to fulfil maintenance as a profit-making centre, Alexandre *et al.* (2008) introduced the excellent-maintenance concept of doing more work with fewer people and less money. They stressed this new generation maintenance concept, which includes:

- (i) Remote maintenance: By leveraging information, wireless and internet technologies, users may log in from anywhere and with any kind of device as soon as they get an internet connection. The maintenance operation team can connect remotely to the equipment in the factory, then run setup, control, configure, diagnose, debug, fix, monitor performance, or download data for analysis;
- (ii) Cooperative or collaborative maintenance: Excellent-maintenance symbolizes the opportunity to implement an information infrastructure connecting geographically dispersed subsystems;
- (iii) Immediate or on-line maintenance: The real-time remote monitoring of equipment status, coupled with programmable alerts, enables the maintenance operator to respond whenever any breakdown occurs. In addition, high-rate communications allow them to quickly obtain several kinds of expertise and to accelerate the feedback reaction in the local loop, connecting the product, monitoring agent and maintenance support system together. It has almost unlimited potential to reduce the complexity of traditional maintenance guidance through on-line guidance, based on the results of decision-making and analysis of product condition;

- (iv) Fault diagnosis or localization: Excellent-maintenance offers experts the ability to perform on-line fault diagnosis, share their valuable experiences with each other, and suggest remedies to the operators if an anomalous condition occurs in the inspected machine. In addition, lock-outs and isolation can be performed and recorded on location. Consequently, the amount of time it takes to communicate a production problem to the potential expert solution provider can be reduced, the quality of the information shared can be improved, and thereby the resolution time reduced. All these factors increase the availability of production and facilities equipment, reduce the mean time taken to repair, and significantly utilize field service resources and costs;
- (v) Repair or rebuilding: Remote operators could, via an electronic connection, tap into specialized expertise rapidly without any travelling or scheduling delays. Downtimes could be conceivably reduced through direct troubleshooting with source designers and engineers. In addition, diagnosis, maintenance work performed, and parts replaced are documented on the spot, through structured responses to work steps displayed on the mobile workstation; and
- (vi) Modification or improvement: The multi-source knowledge and data environment provided by excellent-maintenance allows efficient information sharing. With the availability of tools for interacting, handling, and analysing information about product state, the development of maintenance engineering for product lifecycle support, including maintenance and retirement stages such as disassembly, recycling, reuse and disposal, is becoming feasible.

The excellent-maintenance concept requires a good information technology system. There are very promising developments in information technology, which can help to improve maintenance practice. However, the information system development in maintenance is still relatively young in the business area, and its recent development is discussed in the next section.

2.5 Maintenance Information System

The information system is becoming an important tool for achieving efficiency and effectiveness within maintenance, provided that the correct and relevant information technology is applied. In fact, there are many papers on the maintenance information system and technologies, where they are always integrated with other disciplines such as inventory control, supply chain management and communication technology on the manufacturing shop floor. Here, four reviews are worth discussing under this sub-section. The first review is given by Labib (2004), who discusses the Computerized Maintenance Management System's (*CMMS*) development to facilitate the management of maintenance resources, to monitor maintenance efficiency and to provide appropriately analysed management information for further consideration. Labib (2004) has suggested some benefits that *CMMS* can offer, as follows:

- (i) It allows operators to report faults faster by filling-up the electronic-form. At the same time, it enables the maintenance team to respond to and update the form promptly;
- (ii) It can facilitate improvements in communication between operators and maintenance personnel, and is influential in ameliorating the consistency of information flow between these two departments;
- (iii) It offers insight into wear-and-tear in *FBM* activities;
- (iv) It provides maintenance planners with the historical information necessary for developing next *PM* schedules; and
- (v) It can track the movement of spare parts and requisition replacements whenever necessary.

In the second review, O'Donoghue and Prendergast (2004) proved that *CMMS* is very beneficial. They examined the basis of various maintenance management strategies used to date in international manufacturing. They have demonstrated how *CMMS* is used to capture maintenance activities, and analysed maintenance time and cost in an Irish textile manufacturing company.

Lately, rapid growth in computer technology has opened up new possibilities in *CMMS* development. This brings us to the third review, in which Mirka (2008) reported that *CMMS* provides tremendous benefit to maintenance. She identified salient characteristics of *CMMS* by showing that information technology investment has a positive correlation to company profitability and competitiveness. She also developed information technology tools based on a company's factors of goal and purpose.

Despite providing significant characteristics of *CMMS*, which may fit in with the needs of the industries, Labib (2004) also discovered that the majority of available *CMMS* in the market lack decision support for management. This motivates us to investigate the fourth crucial review, highlighted by Sherif *et al.* (2008). They managed to embed a Decision Support System (*DSS*) into *CMMS* as an advanced software engineering approach. *DSS* constitutes a class of computer-based information systems, including knowledge-based systems that support decision-making activities. A computer program is written using available maintenance techniques to automate the analysis and results. The program is executed in sub-procedures in *CMMS* as a *DSS* module.

Sherif *et al.* (2008) synthesized *DSS* with problem-solving in concrete bridge decks maintenance activities. They proposed different decisions for different types of repair, *i.e.* shallow repair, deep repair, protective repair, non-protective repair, and deck replacement. All decision-makers must consider the cost of repair when making any recommendation. Sherif *et al.* (2008) also deliberated on how *DSS* is used to model human reasoning and the decision-making process for concrete bridge decks. At the end of the study, they concluded that buying sophisticated hardware or software is not the complete answer. However, justification on middleware software, and an object-oriented system by integrating some maintenance techniques into the *DSS*, is another potential area to consider. There are various available techniques in maintenance that can be programmed into *CMMS* and can measure maintenance activities. The techniques are elaborated on in the next section.

2.6 Maintenance Techniques

Palmer (1999) gives two types of maintenance systems to be studied, as shown in Figure 2.3:

- (i) Non-repairable system; and
- (ii) Repairable system.

A non-repairable system is a straightforward system where machines will be used until they are scrapped when they reach a wear-out period such as the battery, light bulb, fuse, tube, *etc.* Whereas, a repairable system is more complicated as it involves repairing, part replacements and reconfiguration of the machine from a failure state back to the operation state such as an engine, cooling fan, compressor, condenser, *etc.* Our study focuses on a repairable system, which is more complex.

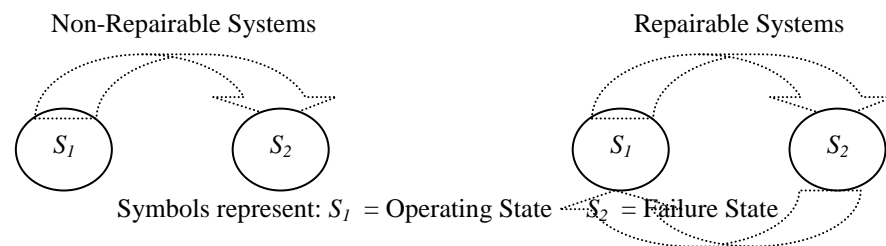


Figure 2.3: Maintenance Systems

Based on Figure 2.3, the goal of the study will be to obtain the longest survival period of a machine at state S_1 , and its transition from state S_1 to S_2 . The service provider that can ensure that the longest transition time from state S_1 to S_2 is preferred. The transition period from the failure state, S_2 back to the operation state, S_1 reflects the maintenance department or technicians' productivities. Obtaining the shortest transition period will be the goal of the study on a machine at state S_2 back to S_1 . The service provider that is able to bring the equipment back from state S_2 to S_1 in

the shortest possible time is considered to be more reliable and will be the choice of vendor. Usually, there are many conflicts occurring between customers and service providers at the transition state from S_2 to S_I .

From the customers' point of view, the transition from S_2 to S_I must be as short as possible regardless of response time, repair time or replacement time, as all these reflect a machine's productivity. However, the service providers always require more time, including some buffer time intervals between S_2 to S_I . This is because they have to consider other constraints or underlying risk factors, such as expertise, budget, tools, waiting time for replacement parts, and other obstacles during troubleshooting activities.

2.6.1 Reliability-centred Maintenance

In 1960 civilian airlines in the United States of America experienced 40 crashes per million take-offs due to premature aircrafts' equipment failure. Then, the initial development of maintenance measures was undertaken by the North American civil aviation industry. More theoretical background was introduced when they realized that many of their maintenance philosophies were poor. This led to a more integrated approach, as it was actively dangerous. In the 1970s, maintenance started to involve a closer linkage to Reliability (R) and Maintainability (M). The terms R and M became very popular, and gave birth to Reliability-centred Maintenance (RCM). RCM is a method for defining the maintenance strategy in a coherent, systematic and logical manner (Amik and Deshmukh, 2006). RCM is a structured methodology for determining the maintenance requirements of any equipment in its operation, and for looking at the way in which equipment fails. In short, RCM is able to measure reliability of maintenance performance in the manufacturing plant. Then, RCM measures it assessing the consequences of each failure and chooses the correct maintenance action at the right time to always meet production-desired levels (Bentley, 1993).

Since reliability of the items is dependent upon time, the repetitive failure is represented by Figure 2.4.

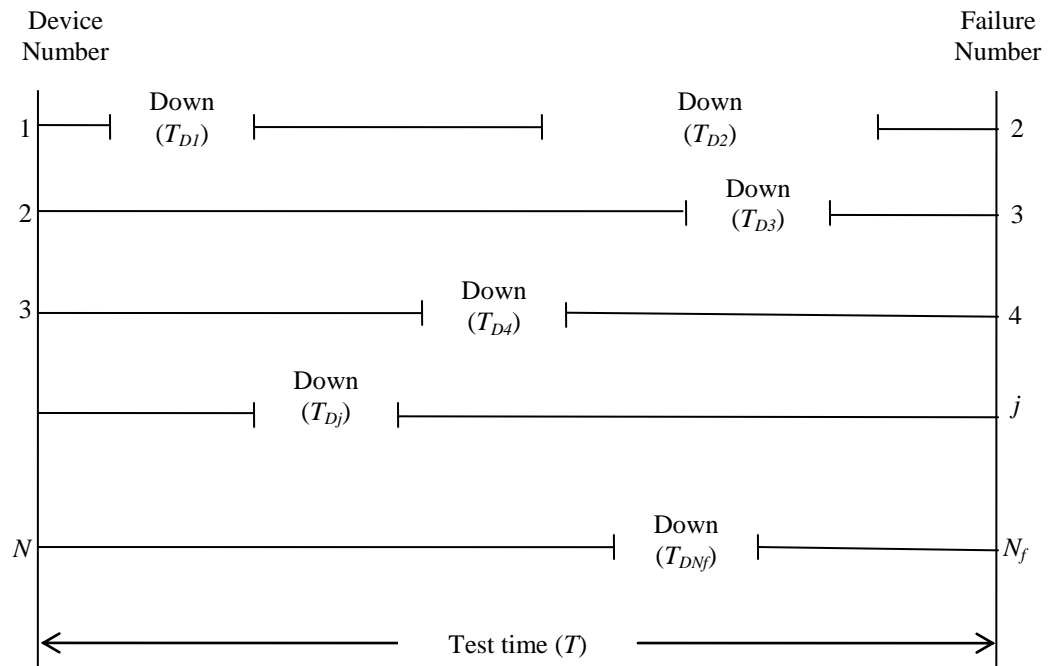


Figure 2.4: Repairable Items Failure Patterns (Bentley, 1993)

Bentley (1993) assumed that N individual items are placed in service and the times at which failures, f , occur are recorded during a test interval, T . Let the downtime T_{Dj} be the total time that elapses between the occurrence of the j th failure and the repair time required to put the equipment back into normal operation. Let N_f be the failure number of the N device during a T interval. Then, certain measures and formulae are derived as follows:

$$\text{Total downtime} = \sum_{j=1}^{j=N_f} T_{Dj}$$

$$\text{Total up time} = NT - \text{Total down time}$$

$$= NT - \sum_{j=1}^{j=N_f} T_{Dj}$$

$$\begin{aligned}
 \text{Mean downtime (MDT)} &= \frac{\text{Total down time}}{\text{Number of failures}} \\
 &= \frac{1}{N_f} \sum_{j=1}^{j=N_f} T_{Dj}
 \end{aligned}$$

$$\begin{aligned}
 \text{Mean time between failures (MTBF)} &= \frac{\text{Total up time}}{\text{Number of failures}} \\
 &= \frac{NT - N_f MDT}{N_f}
 \end{aligned}$$

$$\begin{aligned}
 \text{Mean failure rate (} \boxed{\times} \text{)} &= \frac{N_f}{NT - N_f MDT}
 \end{aligned}$$

The availability of the product is the fraction of the total test interval that it is performing within certain specifications:

$$\begin{aligned}
 \text{Availability} &= \frac{\text{Total up time}}{\text{Test interval}} \\
 &= \frac{MTBF}{MTBF + MDT} \\
 &= \frac{(N_f \times MTBF)}{(N_f \times MTBF) + (N_f \times MDT)}
 \end{aligned}$$

$$\begin{aligned}
 \text{Unavailability} &= \frac{\text{Total down time}}{\text{Test interval}} \\
 &= \frac{MDT}{MTBF + MDT}
 \end{aligned}$$

2.6.2 Lifetime Function

There are several types of lifetime analysis available to observe repair performance and failure patterns. Yang and Chen (2000) measured the service performance index by using an explicit expression to compare the number of complaints that occurred, with the desired target set by a firm. David and Xiao (2002) used an appropriate hypothetical project as the basis for a semi-structured questionnaire survey, for accruing the data required to allow robust statistical analyses to be applied. David and Xiao (2002) applied the Analysis of Variance (ANOVA) technique to compare the service performance between several countries.

Leemis (1995) reported that the statistical reliability function is commonly used to measure the probability and observe failure patterns of the machine in operation at any particular time. At all times, if t is less than 0, the machine's reliability is assumed to be 1. The survivor function, also known as the reliability function, $R(t)$, is the reliability at time t . The complementary cumulative distribution function can be computed for continuous random variables, that is $R(t) = 1 - F(t)$, where $F(t) = P(T < t)$ is the cumulative distribution function. The following properties hold the reliability function, $R(t)$:

- (i) $R(0) = 1$;
- (ii) $\lim_{t \rightarrow \infty} R(t) = 0$; and
- (iii) $R(t)$ is non-increasing.

The reliability function is applied in two ways:

- (i) The probability that an individual item is still functioning at time t , which is denoted as $R(t)$; and
- (ii) $R(t)$ is the expected fraction of the population that is still functioning at time t , for a large population of items with identically distributed lifetimes.

Leemis (1995) defined the conditional reliability function to be $R_{T|T \geq a}(t)$, given that the machine has operated until time a . Next, it is useful to compute the probability of the machine functioning beyond a to another time of $T = t$. This can be represented using the conditional probability as follows (Leemis, 1995):

$$R_{T|T \geq a}(t) = \frac{P(T \geq t \text{ and } T \geq a)}{P(T \geq a)} = \frac{P(T \geq t)}{P(T \geq a)} = \frac{R(t)}{R(a)}, \quad t \geq a$$

2.6.3 Hazard Function

The hazard function is the ratio of the probability density function towards reliability function. It is widely used for the following reasons (Leemis, 1995):

- (i) It indicates the amount of risk associated with the machine at a particular time, t ;
- (ii) It can be used to compare the way risk changes over time for several populations of machines. This can be done by plotting their hazard functions using graphical representations; and
- (iii) The hazard function can be shown as a type of intensity function, which can be employed to explain many other stochastic processes. It can be used as a baseline function for deriving failure regression measures.

The hazard function is known as the failure rate in machinery maintenance and is always represented by λ . Leemis (1995) derives the hazard function using the conditional probability of failure between times t and $(t + \Delta t)$ as follows:

$$P(t \leq T \leq t + \Delta t) = \int_t^{t+\Delta t} f(\tau) d\tau = R(t) - R(t + \Delta t)$$

The conditional probability of the occurrence of an event for small values of Δt is given as (Leemis, 1995):

$$h(t) \Delta t = P(t \leq T \leq t + \Delta t \mid T \geq t)$$

Leemis (1995) classified the hazard function, $h(t)$, as:

- (i) The constant failure rate (λ) as shown in Figure 2.5, where failure rate is λ . This is the reliability function of the exponential distribution, $R(t) = e^{-\lambda t}$. Any failure of the machine can be considered as new and independent of any previous failure histories;



Figure 2.5: Constant Value Failure Rate

- (ii) Decreasing failure rate is shown in Figure 2.6. This intensity function is sometimes observed in the production line where low quality components are likely to fail early. Some tests in the burn-in section will help to remove these defective items in the initial stages;

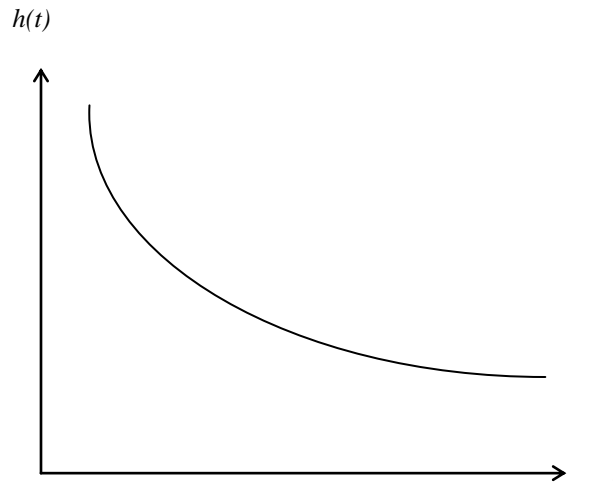


Figure 2.6: Decreasing Failure Rate

- (iii) Increasing failure rate is shown in Figure 2.7. This is most common in the analysis of machine life problems. The unit is subjected to ageing by accumulated damage through wear over time. The hazard function is increasing over time;

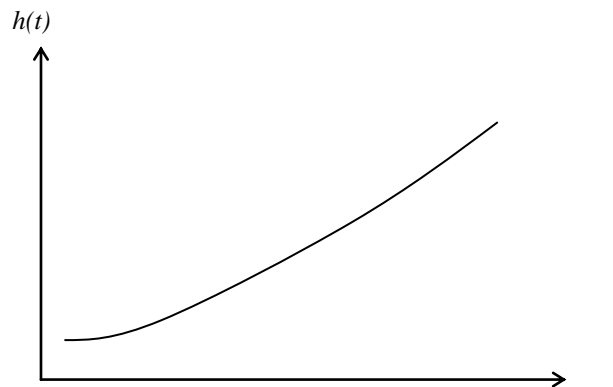


Figure 2.7: Increasing Failure Rate

- (iv) The bathtub failure rate hazard function is shown in Figure 2.8. In the initial stage, the failure rate decreases. This is called infant mortality. Then, it is constant for a certain interval in the middle, which is called the useful lifetime. In the final stage, the failure rate increases, and this

is considered as the wear-out period. In the maintenance area, it is not practical to model the complete bathtub curve in a sophisticated way. Different maintenance strategies have to be applied at certain stages depending on the machines' background and their utilization.

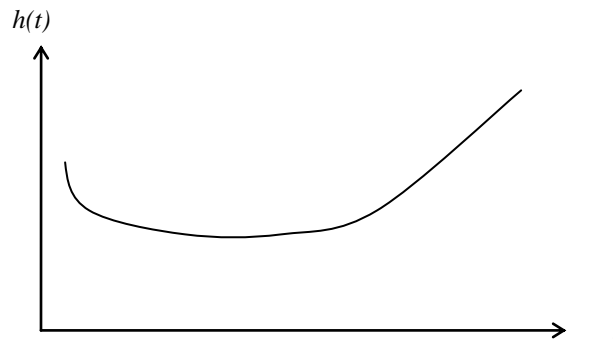


Figure 2.8: Bathtub Failure Rate

2.6.4 Non-Parametric Measures

Non-parametric means that the reliability function need not be from a known parametric distribution, such as the exponential, weibull, gamma, normal, *etc.* There are a few different types of non-parametric methods used extensively to estimate the reliability function, $R(t)$. One of the most famous is the Product Limit method, introduced by Kaplan and Meier (1958), which has been used mostly in epidemiology and reliability analysis.

The Product Limit method is used to compute and plot the empirical reliability function of univariate data over time. Suppose there are n items in operation with the possibility of multiple failures, with f_i being the number of failures recorded at time t_i under study. Divide the time axis $[0, \infty)$ into $k + 1$ intervals as:

$I_i = [a_{i-1}, a_i)$, $i = 1, 2, \dots, k + 1$, with $a_0 = 0$, $a_k = T$, and $a_{k+1} = \infty$, where T is an upper limit of observation (Lawless, 1982). Let t_i be the right endpoint of I_i , which is the i th ordered observation of either censored or uncensored observations. $T_{(1)} < T_{(2)} < \dots < T_{(n)}$ can be considered as the ordered statistics of T_1, T_2, \dots, T_n , where T_i is the variable for the i th time for either censored or uncensored data. Then, the corresponding censored or uncensored values are $t_{(1)} < t_{(2)} < \dots < t_{(n)}$. If n items are observed and p is the total number of censored cases, then $(n - p)$ is the number of uncensored cases that are observed. The pairs of $(T_1, \delta_1), (T_2, \delta_2), \dots, (T_n, \delta_n)$ can be observed, respectively,

$$\text{where } \delta_i = \begin{cases} 0, & \text{if } T_i \text{ is censored,} \\ 1, & \text{if } T_i \text{ is uncensored.} \end{cases}$$

Bunday (1991) gives the estimate for the reliability function as:

$$\widehat{R}(t) = \prod \left(1 - \frac{f_i}{n_i} \right)^{\delta_i}$$

2.6.5 Product Limit Stratification

Often, it is of interest to determine whether two or more samples could have arisen from identical reliability functions. There may be some sub-populations under study, which may consist of a number of their own hazard functions respectively. Stratification analysis can be used to adjust such sub-population differences. There is more than one variable that can be specified for stratification, and the corresponding variables are formed by a combination of levels (Kalbfleisch and Prentice, 1980). Let $t_1 < t_2 < \dots < t_k$ denote the failure times for the sample formed by a set of r individual samples. Suppose f_j failures occur at t_j , λ_j is the failure rate at t_j and n_j study subjects are at risk just prior to t_j ($j = 1, \dots, k$). Let f_{ij} and n_{ij} be the corresponding numbers in sample i , where $i = 1, \dots, r$. The data at t_j are in the form of a $2 \times r$ contingency table with f_{ij} failures and $n_{ij} - f_{ij}$ survivors in the i th row ($i = 1, \dots, r$).

Conditional on the failure and censoring experience up to time t_j , the distribution of f_{1j}, \dots, f_{rj} is simply the product of binomial distributions (Kalbfleisch and Prentice, 1980):

$$\prod_{i=1}^r \binom{n_i}{f_{ij}} \lambda_j^{f_{ij}} (1 - \lambda_j)^{n_i - f_{ij}}$$

where λ_j is the conditional failure probability at t_j , which is common for each of the r samples under the null hypothesis.

2.6.6 Competing Risk Analysis

Factors that contribute to the delay in repair time during a breakdown can be categorized into classes. In respect of troubleshooting performance, all the technicians can take a challenge to see who can repair the failure faster. In general, the technicians have their own way of bringing the failed equipment back to the operation condition as fast as they can. Under these conditions, component reliability is the product of the repair time reliabilities, and the component failure rate is just the sum of the failure mode failure rates.

Jayant and Sudha (2001) extended the Product Limit method to estimate the competing risks of the censoring variable of the system's lifetime. The method will be applied separately to each failure mode within the data set, considering failures due to all other modes as censored run times. Assume a repairable unit has k different ways in which it can be repaired by individuals. An event is assumed to be in k classes, with the respective competing risks C_1, C_2, \dots, C_k . The competing risks model can be used to combine maintenance performance to form more complicated models to measure the individual lifetimes, by considering the presence of all other risks. The model considers sojourn times, where the individuals in a population can spend time in a different state, with the possibility of being censored in the list of states of interest. Let probability matrix, $P = (p_{ij})$: that is, p_{ij} is the probability of the system entering state j next, having just entered state i . Using this exercise, all the states are

visited to obtain the reliability measures (Lawless, 1982). The Product Limit reliability estimate for the competing risks analysis is shown by:

$$\hat{R}(t) = \prod_{l: t_l < t} \left(\frac{n_{il} - f_{il}}{n_{il}} \right)$$

where $t_{i1} < t_{i2} < \dots < t_{ir_i}$ are the distinct ordered sojourn times in state i of all individuals, and n_{il} and f_{il} are the numbers at risk and the number of sojourn times at t_{il} . For instance, when there is no censoring present, p_{ij} can be estimated as the proportion of cases in which individuals that entered state i proceed to state j . Islam (1994a) and Burhanuddin (2003a) have extended this methodology in a multistate environment, to estimate unequal probabilities for uncensored and censored cases.

2.6.7 Semi-Parametric Measures

Semi-parametric approach, the Proportional Hazards Model (*PHM*), was introduced by Cox (1972). Then, the model was extended with some parallel approaches when considering time-dependant covariates (Cox and Oakes, 1984). The *PHM* is used frequently for failure time analysis, because of its robustness in estimating reliability curves with unspecified baseline functions. It allows us to estimate the hazards and risks of interest for individuals, given their prognostic variables. The model is able to provide an estimate of the troubleshooting performance on reliability measures after adjustment of other explanatory variables.

This approach is suitable for downtime analysis as it is able to estimate several explanatory variables simultaneously. By fitting this model to the breakdown data, the estimates for the impact of some risk factors before the equipment fails can be obtained. Even if the breakdown terms are similar in respect of the variables known to the reliability effect, using *PHM* with these prognostic variables may produce a more precise estimate of the troubleshooting performance, for example, by narrowing the confidence interval and likely estimates. This provides the guidelines

for adjusting the existence of certain risk factors as a milestone to improve the reliability of the maintenance operation.

The variables can be represented as a vector of covariates, $\mathbf{Z} = (Z_1, Z_2, \dots, Z_p)$. The corresponding vector of regression parameters can be represented as $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_p)$. The general form of the proportional hazards function is:

$$h(t, z) = h_0(t) g(z)$$

Baseline hazard function is $h_0(t)$ and $g(z)$ is the exponential expression for the sum of the corresponding explanatory variables (Kleinbaum, 1996). The explanatory variables can be either continuous or discrete.

The reliability function, $R(t)$, can be obtained as $R(t; \mathbf{Z}) = P(T \geq t | \mathbf{Z} = \mathbf{z})$, where T is the associated failure time. Let \mathbf{Z} denote the regression vector of explanatory variables (Z_1, Z_2, \dots, Z_p) with t being the associated failure time. Let $\boldsymbol{\beta}$ denote the vector of unknown regression parameters associated with the explanatory variables, $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_p)'$, then the hazard relationship is (Lawless, 1982):

$$\begin{aligned} h_i(t) &= h(t | \mathbf{z}) = h_{0i}(t) e^{(\mathbf{Z}\boldsymbol{\beta})}; i=1, 2, \dots, \text{ or} \\ \log[h_i(t)] &= \log[h_{0i}(t)] + (\mathbf{Z}\boldsymbol{\beta}); i=1, 2, \dots \end{aligned}$$

The assumption of a constant hazard ratio is called the proportional hazards assumption. The set of parameters $h_{0i}(t)$ is called the baseline hazard function, whose purpose is merely to control the explanatory variables of interest, $\boldsymbol{\beta}$, for any changes in the hazard over time.

The reliability function is given by Kalbfleisch and Prentice (1980) as:

$$R(t; \mathbf{z}) = e^{-\int_0^t h_0(\tau) e^{\mathbf{z}\boldsymbol{\beta}} d\tau}$$

The formula for the *PHM* likelihood function is always called a partial likelihood function rather than a complete likelihood function. This is because the likelihood formula only considers probabilities for those subjects that fail, and does

not explicitly consider probabilities for those censored subjects. In particular, Kleinbaum (1996) defined the partial likelihood as the products of several likelihoods, one for each of, say, n failure times. Thus, at the i th failure time, L_i denotes the likelihood of failing at this time, given that the machine has already survived up to this time. This can be represented as:

$$L = L_1 \times L_2 \times L_3 \times \dots \times L_n = \prod_{i=1}^n L_i, \text{ where } L_i \text{ is the portion of } L \text{ for the } i\text{th}$$

failure time.

Let \mathbf{Z}_l denote the vector of explanatory variables for the l th individual. Let $t_1 < t_2 < \dots < t_k$ denote the k distinct, ordered event times. Let f_i denote the multiplicity of failures at event time, t_i . That is, f_i is the size of the set F_i of individuals that fail at t_i . Let S_i be the sum of the vectors \mathbf{z}_l over the individuals who fail at t_i , that is, $\sum_{l \in F_i} \mathbf{z}_l$.

Let R_i denote the risk set just before the i th ordered event time t_i . Let R_i^* denote the set of individuals whose event or censored times exceed t_i , or whose censored times are equal to t_i . Then, the exact type of partial likelihood function is (SAS Institute Inc, 1999):

$$\prod_{i=1}^k \left\{ \prod_{j=1}^{f_i} \left[1 - e^{-\frac{e^{(\mathbf{z}_j \boldsymbol{\beta})}}{\sum_{l \in R_i^*} e^{(\mathbf{z}_l \boldsymbol{\beta})}} t} \right] e^{(-t)} dt \right\}$$

The coefficients for each covariate can be examined. A positive regression coefficient for an explanatory variable means that the hazard is higher. This implies that the prognosis is worse for higher values. Conversely, a negative regression coefficient implies a better prognosis for higher values of the variable. The *PHM* requires that for any two covariate sets \mathbf{z}_1 and \mathbf{z}_2 , the hazard functions are related (Kalbfleisch and Prentice, 1980):

$$h(t; \mathbf{z}_1) \propto h(t; \mathbf{z}_2), 0 < t < \infty$$

Although this relationship is descriptive of many situations, sometimes there are important factors, and the different levels of these produce hazard functions that differ markedly from proportionality.

The proportionality for each variable can be examined. The p -value for evaluating a proportional hazards assumption for each variable in the model is derived from a standard normal statistic, $N(0,1)$, which is computed from the model output (Kleinbaum, 1996). A non-significant, *i.e.* large p -value, say greater than 0.1, indicates that the proportional hazards assumption is satisfied, whereas a small p -value, say less than 0.05, indicates that the variable being tested does not satisfy this assumption. If the subjects fall into different groups, and we are not sure whether we can make the assumption that the group's hazard functions are proportional to each other, we can estimate separate log cumulative hazard functions for the groups using a stratified model (Kleinbaum, 1996). Burhanuddin (2003b) applied the *PHM* in air conditioning maintenance work. He measured a delay in the air conditioning's troubleshooting work using a multivariate analysis.

Later, Albert *et al.* (2006) optimized condition-based monitoring decisions using the *PHM* approach. They have proved that the model is perfect to formulate motor transmission equipment, power transformers and manufacturing processes. They also examined the significant issues of data management in *CBM* decision analysis. In particular, Albert *et al.* (2006) captured data from two common condition monitoring techniques, *i.e.* vibration monitoring and oil analysis.

2.6.8 Stratified Proportional Hazards Model

The population under study may consist of a number of sub-populations, each with its own baseline hazard function. Stratification analysis can be used to adjust such sub-population differences. Stratification can be used to control certain variables or predictors that do not satisfy the proportionality assumption. Predictors that are

assumed to satisfy the proportionality assumptions are included in the model, while the predictor being stratified is not included (Kleinbaum, 1996).

A single new variable can be defined to perform the stratified proportional hazards procedure. Let k be the variables not satisfying the proportional hazards assumption and p be the variables satisfying the proportional hazards assumption. We can denote the variables not satisfying the proportional hazards assumption as Z_1, Z_2, \dots, Z_k and Y_1, Y_2, \dots, Y_p for the variables that are satisfying the proportional hazards assumption. A single new variable from the Z s, which we call Z^* , can be defined and used for stratification. We do this by forming categories of each Z_i including those Z_i 's that are interval variables. We then form combinations of categories, and these combinations are our strata. These strata are the categories of the new variable Z^* .

The stratification variable Z^* will have k^* categories, where k^* is the total number of strata formed after categorizing each of the Z 's. The fitted stratified *PHM* will yield different estimated reliability curves for each stratum, because the baseline hazard functions are different for each stratum. However, because the coefficients of the Y s are the same for each stratum, the estimates of hazard ratios remain the same for each stratum (Kleinbaum, 1996).

Then, the general hazard function form for the stratified model can be derived. The hazard function for the j th individual in the i th stratum is expressed as (Lawless, 1982):

$$h_{ij}(t) = h_{i0}(t) e^{(z_{ij}\beta)} ; i = 1, 2, \dots, k$$

where $h_{i0}(t)$ is the baseline function for the i th stratum and z_{ij} is the vector of explanatory variables for the j th individual. The partial likelihood has the form of:

$$\log[h(t)] = \log[h_0(t)] + (Z\beta)$$

However, the risk set for a failure is not confined to subjects in the same stratum. The regression coefficients are assumed to be the same for all individuals across all strata.

2.6.9 Censoring

Sometimes, lifetime data are incomplete and precise lifetimes are uncertain for some individuals, although we know that they have survived beyond a certain time. Such an item is said to be censored. Censoring can arise for a variety of reasons. Kleinbaum (1996) gives three reasons why it may occur:

- (i) A machine or person does not experience the event before the study ends;
- (ii) A machine or person is lost to follow-up during the study period; and
- (iii) A machine or person is withdrawn from the study because of some reason.

The most frequent type of censoring is known as right censoring and it is divided into two types: Type *I* and Type *II* censoring. In a right-censored dataset, there are one or more items for which only the lower bound is known. Bunday (1991) stated that Type *I* censoring occurs when n items are observed for limited periods L_1, L_2, \dots, L_n . A predetermined time, T_i , for ending the study has been fixed and the number of exact lifetimes observed is random. Then, for the i th individual, the failure observation will be at time T_i if $T_i \leq L_i$ and L_i if $T_i > L_i$.

Type *II* censored data only arises when the r smallest lifetimes (from the n) are observed. The n items are tested but the decision is made at the outset to terminate the test at the time when the r th failure occurs. Let f_j be the number of individuals who fail in interval I_j , for $j = 1, 2, \dots, k$. Let n_j be the number of individuals still functioning at time t_{j-1} . Let c_j be the number of individuals censored during I_j . Then, $n_j = n_{j-1} - f_{j-1} - c_{j-1}$ denotes the number of individuals still functioning at the start of I_j . If all the censored items were censored at the end of I_j , then n_j items would be at risk during I_j . If all the censored items were censored at the start of I_j , then $n_j - c_j$ items would be at risk during I_j .

In machine testing and experiments, there are periodic inspections for the proper functioning of every parts of the equipment. The periodic follow-up period is

defined as being between an interval. Such interval censoring occurs periodically and the failure time falls in some intervals (L_i, R_i) , where L_i represents the left end point and R_i is the right end point of the censoring interval.

2.6.10 Maintenance Scheduling

Scheduling maintenance activities requires justification, as it contributes to cost, staff, safety and other criteria. Maintenance scheduling is classified into two major categories (Duffua and Sultan, 1999):

- (i) Preventive and routine maintenance; and
- (ii) Scheduled overhauls and corrective maintenance.

The first category can be planned and scheduled easily, but the second one is of a stochastic nature, which makes maintenance scheduling a challenging problem and distinguishes it from production scheduling. A realistic schedule must consider both categories. The main issues in maintenance scheduling are (Duffua and Sultan, 1999):

- (i) Job completion time;
- (ii) Availability of equipment for performing maintenance job;
- (iii) Availability of technical personnel to conduct maintenance job; and
- (iv) Machinery and the efficiency of spare parts delivery at job sites.

To accomplish the maintenance issues above, there are important decision parameters in maintenance scheduling (Duffua and Sultan, 1999):

- (i) Equipment downtime;
- (ii) Idle time of technicians and machines;
- (iii) Downtime cost;
- (iv) Total scheduling time;

- (v) Equipment availability;
- (vi) Number of jobs completed in a given time; and
- (vii) Job skill requirement, sequence and availability.

Most practitioners tend to use stochastic approaches and mathematical modelling to estimate the parameters and schedule maintenance work in an uncertain environment. Duffua and Sultan (1999) used the stochastic programming model to schedule maintenance personnel. They have shown a ten percent improvement in the deterministic formulation of the maintenance scheduling problem. Stochastic programming is a mathematical program, where some of the data incorporated into the objective and the constraints are uncertain. Uncertainty can usually be characterized by developing a probability distribution function from known parameters.

Hakan *et al.* (2007) discussed another important aspect of maintenance scheduling when dealing with maintenance outsourcing work. In outsourcing, the maintenance workload is transferred to outsiders, with the goal of reducing the number of full-time equivalents. By outsourcing, the company can re-organize the resources to concentrate on other core competencies of the business. This led to another challenge regarding how to build an appropriate formulation to measure a contractor's maintenance performance.

2.6.11 Maintenance Performance

There are some pitfalls relating to the indiscriminate use of common maintenance performance in real-life applications. Albert *et al.* (1999) compared some performance measures and concluded that the balance scorecard shows the best performance measures in maintenance management. The balance scorecard is a vehicle that translates a business' mission and strategies into a set of objectives and quantifiable measures, built around four perspectives (Albert *et al.*, 1999):

- (i) Investor's views from a financial perspective;
- (ii) The performance attributes valued by customer perspective;
- (iii) Internal processes and procedures to achieve business objectives; and
- (iv) Learning and growth means the capability to improve and create values.

As a result, it directed managers to focus on the most critical measures for the continual success of the organization. Based on these perspectives, we are able to measure indicators such as the Key Performance Index (*KPI*) and some examples given by Albert *et al.* (1999) are shown in Table 2.1.

Table 2.1: Key Performance Index for different Perspectives (Albert *et al.*, 1999)

Perspective	Strategic objective	Key Performance Indicator
Financial	Reduce operation and maintenance costs	<ul style="list-style-type: none"> • Operation costs per customer • Maintenance costs per customer
Customer	Increase customer satisfaction	<ul style="list-style-type: none"> • Customer loss • Customer satisfaction rating
Internal processes and procedures	Enhance system integrity	<ul style="list-style-type: none"> • Percentage of time exceeds limits • Number of contingency plans reviewed
Learning and growth	Develop a multi-skilled and empowered workforce	<ul style="list-style-type: none"> • Percentage of cross-trained staffs • Hours of training per employee

Later, Kutucuoglu *et al.* (2001) formulated more *KPI* measures after classifying maintenance performance into five main categories, as follows:

- (i) Equipment-related performance;
- (ii) Task-related performance;
- (iii) Cost-related performance;
- (iv) Immediate customer impact-related performance; and
- (v) Learning and growth-related performance.

They have provided links between actual output and the desired results, to ensure that there are minimum conflicts with the business' overall needs. Kutucuoglu *et al.* (2001) developed a framework for maintenance performance measurement using quality function deployment techniques. They have modified certain *KPI* to fulfil those five main categories in North West cabling product companies in the United Kingdom.

Mary and Frank (2004) used the performance measurement framework model developed by Kutucuoglu *et al.* (2001) in management control, resource-based, system-based and contingency-based strategies. Then, they extended the model to improve profitability of the company. The performance measurement model in maintenance includes multiple performance measures relevant to the distribution channel for products, repair parts and services. Mary and Frank (2004) have addressed four research questions in their study as follows:

- (i) Are measure attributes important considerations for performance measure choice?
- (ii) Does the importance of attributes differ according to a firm's strategies?
- (iii) Does the importance of attributes for design and use differ according to a firm's strategies? and
- (iv) Does a company trade off some individual attributes for others?

To answer the above research questions, they utilized both a qualitative and quantitative approach, and analysed archival documents quantitatively. Subsequently, they applied a qualitative approach by conducting interviews with top managers to understand the nature of the business, the objectives, and the dynamic structure of the company's organization. Finally, Mary and Frank (2004) produced some implications of performance measurement and maintenance control.

An attempt should be made to ascertain that the performance of the machines and maintenance personnel are being fully utilized. Eti *et al.* (2004) considered some Total Productive Maintenance (*TPM*) approaches for improving maintenance performance. *TPM* has been developed in Japan, and is a long-term program to

increase skills, raise efficiency and achieve zero losses. Maintenance engineers and operators work in small teams to achieve continuous improvement of the production lines. *TPM* gives operators the opportunities to gain the knowledge and manage their own machines. Instead of waiting for technicians or maintenance engineers to fix all the problems, they try to solve simple problems before they become big ones. Operators conduct basic troubleshooting and then eliminate the root causes of machine minor errors before they become major ones. *TPM* is a part of total quality management, and has these objectives (Nakajima, 1988):

- (i) To maximize equipment effectiveness through the optimization of equipment availability, performance, efficiency and product quality;
- (ii) To establish a maintenance strategy for the life of the equipment;
- (iii) To cover all departments, such as the planning departments, operators and maintenance departments;
- (iv) To get all personnel, from top management to shop floor workers, to participate actively in production issues; and
- (v) To improve maintenance through small group autonomous activities.

In order to achieve zero breakdowns and zero defects, Eti *et al.* (2004) made an effort to implement *TPM* in Nigerian manufacturing industries by:

- (i) Refining preventive and predictive maintenance activities;
- (ii) Focusing on reliability and maintainability engineering;
- (iii) Upgrading every operator's skills;
- (iv) Increasing operator involvement and ownership of the process;
- (v) Improving problem-solving by the team;
- (vi) Maximizing equipment effectiveness;
- (vii) Raising the morale of the team that is involved in the *TPM* program;
- (viii) Improving quality;
- (ix) Increasing safety; and
- (x) Reducing costs.

Later, Eti *et al.* (2006) enhanced their study by providing some strategies in maintenance to measure performance indicators for Nigerian industries, as follows:

- (i) Equipment performance, such as availability, reliability and overall equipment effectiveness;
- (ii) Process performance, such as the ratio of planned to unplanned work, or scheduled compliance; and
- (iii) Cost performance, such as the costs for labour, materials and maintenance.

They have demonstrated some quality function deployment using the Total Planned Quality Management (*TPQM*) program. *TPQM* systemizes all preventive, predictive, and corrective maintenance, plus the control of maintenance quality control. In *TPQM*, maintenance strategies should contain consideration of the following elements (Eti *et al.*, 2006):

- (i) Maintenance organization and management;
- (ii) Measures of effectiveness;
- (iii) Work control;
- (iv) Maintenance management information system;
- (v) Personnel records regarding competencies;
- (vi) Technical documentation;
- (vii) Logistic support;
- (viii) Maintenance tasks; and
- (ix) Maintenance engineering.

In fact, *TPM* has been practiced aggressively in industries, and some examples are given in Table 2.2.

Table 2.2: Applications of *TPM*

Researcher	Focus	Industry	Approach
Swanson (2001), Kristy <i>et al.</i> (2001)	Maintenance strategies improvement, Just-in-Time maintenance and Total Planned Quality Management	Electronics, metal working industries, transportation parts and suppliers	Statistical methods
Chan <i>et al.</i> (2005), Panagiotis (2007)	Improve product quality, a safer working environment, tangible and intangible benefits from <i>TPM</i> implementations	Electronics and food industries	Mathematical formula on availability, performance efficiency, quality rate and overall equipment effectiveness, pareto distributions
Marcelo and Kazuo (2006)	Factors that damage <i>TPM</i> success	Machineries and electronics industries	Qualitative analysis through observation and interviews
Ashayeri (2007)	Development of the computer-aided maintenance resource planning	High precision computer numerical control and machining centres	Software development

Liu *et al.* (2007) presented a new method that is capable of achieving higher long-term prediction accuracy by comparing signatures from any two degradation processes, using measures of similarity that form a match matrix. The match matrix concept enables inclusion of large amounts of historical information into the prediction of the current degradation process. Once the match matrix between performance and its behaviour in the current run is predicted, then the signatures in each of the M past runs matrices can be constructed, with each match matrix yielding a time series of the mean indices of the best match.

Future values of mean best match indices can now be predicted using a linear parametric technique, the Auto-Regressive Moving Average (*ARMA*) model based prediction. The *ARMA* modelling method allows analytical expression for the variance of prediction errors and can therefore yield uncertainty or confidence intervals for the prediction of the mean best match indices. The predicted value of the best match index in a given match matrix is the index of the feature vector in the

corresponding past run, and is more likely to be similar to the feature vector of the current run in the future. The model is able to measure process performance in predictive and corrective maintenance. It uses some computer-aid with Recurrent Neural Network for process performance prediction (Liu *et al.*, 2007).

2.6.12 Maintenance Techniques in Risk Analysis

Despite the various maintenance methods discussed above, practitioners are undertaking efforts to discover and deploy more and more techniques for continuous improvement in industries and to save maintenance costs. Traditionally, many companies employ reactive strategies, corrective or failure-based maintenance (*FBM*), and only repair the machines when they fail. *FBM* is conducted in the following ways (Adamantios and Zhao, 2005):

- (i) Perfect repair: a maintenance action that restores the system's operating condition to be *as good as new*;
- (ii) Minimal repair: a maintenance action that restores the system operating state to be *as bad as old*;
- (iii) Imperfect repair: a maintenance action that restores the system operating state to be somewhere between *as good as new* and *as bad as old*;
- (iv) Worse repair: a maintenance action that makes the operating condition worse than that just prior to the failure; and
- (v) Worst repair: a maintenance action that makes the system fail or break down non-deliberately.

Perfect repair is the ultimate way, and requires more diagnosis during troubleshooting, complete testing and analysis after fixing the failure. A reduction in downtime contributes to better reliability of operation on the production shop floor and reflects on the effect of the functional group on reactive maintenance. There are many studies measuring proactive and reactive maintenance strategies using

mathematical modelling. The advantage of a mathematical and statistical investigation is that it gives a much clearer estimate of the relationships between and the influence of the factors involved. The result can provide obvious advantages by establishing data collection procedures to achieve perfect repair activities.

The status of machines that are being repaired can be represented using a state diagram, as shown in Figure 2.9. The system may be in one of the states at any time, where the first letter of the symbol denotes the mode of the unit and the second corresponds to the working state of the unit. Ideally, a company expects the first level support team to perform regular breakdown maintenance on a failed unit at state S_1 and return it back to normal operation at state S_2 . However, once the unit experiences a transition to states S_3 , S_4 or S_5 , there is a high possibility of delay and it varies on the basis of the significant risk factors that exist prior to the occurrence of an event. These are unresolved problems where the categories are special cases that need to be focused on in this study.

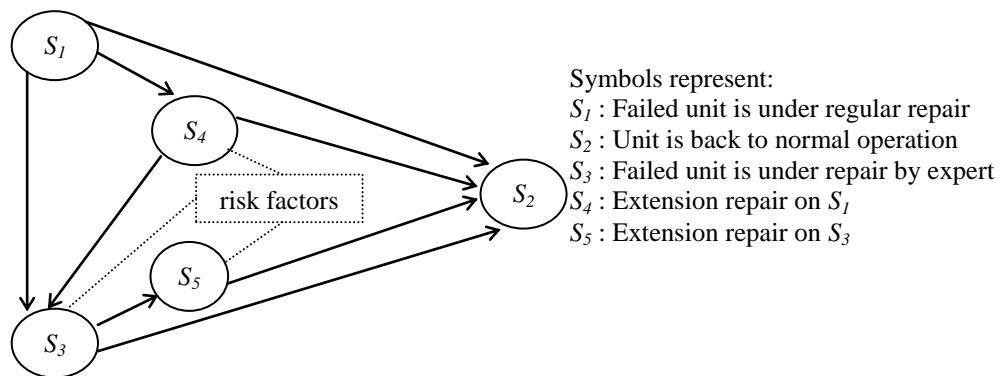


Figure 2.9: Repairing Delay State Diagram

Islam (1994b) demonstrated systematic measurement of risk factors, which can be illustrated with the use of the multistate hazards model for transitions and reverse transitions, among more than one transient state, emerging from the follow-up studies. He discussed the extension of the *PHM* in a multistate environment. The model was used to analyse transitions in contraceptive use over time. Next, a score test was done on the equality of parameters for the model on transitions and repeated

transitions, by considering all the transition states to estimate the repeated measures:

$$\lambda(t, j | i, X(t)) = \lambda_{0ij}(t) \exp(\beta'_{ij} X(t))$$

where λ is the failure rate, i is the origin state ($i = 1, 2, \dots, n$) and j is the transition state ($j = 1, 2, \dots, n + 2$), that occur at time t . The first n states are transient and the states $n + 1$ and $n + 2$ denote censoring and death respectively. β'_{ij} is the vector of coefficients for the transition from i to j , with $X(t)$ as the corresponding set of risk factors (Islam, 1994b).

Based on Figure 2.9, the risk factors may cause a delay in the repair time from S_1 to S_3 and their transition to S_5 . They may also cause a delay time in the transition from S_1 to S_4 and their transition to S_3 . The risk factors might be due to reasons such as technical competency, age, experience or training background of the technical support personnel. They could also be due to ageing or a bad record of previous preventive maintenance on the unit itself. Other obstacles could include a delay in ordering the replacement parts. A good computerized decision support system can help to capture information on these underlying factors effectively. Choy *et al.* (1996) modelled a computerized *DSS*, with a collective approach, as a working tool in assisting the reliability engineer with maintenance. They managed to combine parametric and non-parametric collective approaches. The model is suitable for a complex system with the existence of multiple risk factors.

Equipment may experience multiple failures with multiple risk factors at a particular breakdown, and which of these failures should be resolved first by the technical crew is a concern. Braglia (2000) explained the potential causes of failure and their effects using the Multi-Attribute Failure Modes Analysis. The ranking of the causes of failure is obtained by using qualitative pairwise matching with the Failure Mode Effects and Criticality Analysis (*FMECA*) technique. By following the procedures, Braglia (2000) approximated the final ranking for the failure using the Multi-Attribute Failure Modes Analysis approach. In *FMECA*, Braglia (2000) calculated the criticality number using the formula:

$$CN_i = \alpha_i \times \beta_i \times \lambda_i \times t$$

where CN_i is the criticality number, α_i is the failure mode ratio, β_i is the failure-effect probability, λ_i is the part failure rate, and t is the operating time. The criticality number calculation technique is widely used in the nuclear, aerospace and chemical industries. Braglia (2000) has estimated the risk priority number using linguistic terms to rank the chances of the failure modes, with a numeric scale from 1 to 10. The risk priority number (*RPN*) is given by:

$$RPN = S_f \times S_d \times S$$

where S_f is the chance of a particular failure-mode occurrence, S_d is the chance of a particular failure mode being undetected, and S is the severity of the failure effect.

Later, Sankar and Bantwal (2001) derived *RPN* measures to prioritize the repairing actions of failures using *FMECA*. Potential failure detection can be estimated by listing failure effects horizontally and failure causes vertically. *RPN* and Risk Priority Ranks (*RPR*) can be assigned accordingly. Items with a higher *RPR* will be given more priority for corrective actions. Sankar and Bantwal (2001) re-defined the *RPN* differently to help in identifying the most serious risk for remedial action.

Their definition of *RPN* is $RPN = S \times O \times D$, where S (severity) is the seriousness of a group of effects, O (occurrence) is the likelihood that a cause will create the failure associated with those effects, and D (detection) is the ability to detect the failure before it gets to the customer. The item with the highest effect of the failures will be repaired first, followed by the next highest risk in the priority rank. Different maintenance policies and approaches can be applied to equipment on the basis of these functional priorities and complexities in the production lines. This approach is not practical for this research work, as most of the machines in *SMI* production lines are connected in a serial line and carry almost similar priorities.

Desa and Christer (2001) presented quantitative modelling in the absence of objective data in maintenance. Breakdown studies on local bus transportation were analysed. The authors introduced a snapshot modelling approach. It entailed the collection of objective and subjective data, including types, areas, causes and consequences of faults, and means of prevention. The dataset was collected via a

survey from both breakdown and defect repair interventions. Along with the collection of the dataset, snapshot modelling was developed to estimate the delay time performance for every fault type.

Today, studying the performance in breakdown delay becomes a crucial matter as it directly reflects the maintenance team's reputation. Thus, Ahmed (2002) proposed a novel framework, which consists of a number of critical and strategic functions of organizations. Generally, a few functional purposes and values were revised, including performance measurement. Prasad and Rao (2002) extended the breakdown performance study using *PHM* for a renewal process, and a homogeneous and non-homogenous repairable system with the application of the Poisson process. Their studies show that some types of failure were assigned as covariates to estimate the hazard ratios accordingly, using *PHM* to evaluate risk factors in different operating conditions.

Kumar *et al.* (1996) introduced Taguchi's robust experimental design technique to improve service performance. Signal to noise ratio was introduced as an indicator to optimize the process parameters. The orthogonal arrays allow the concurrent variations of all the contributing factors to be evaluated independently. The 80-20 rule, which states that twenty percent of the defects account for eighty percent of the quality loss, is applied to minimize the number of experiments necessary to study the effects of various factors on a process' performance. This provides a good estimate to identify the risk factors scientifically. However, these barriers should be considered when applying the Taguchi methods (Kumar *et al.*, 1996):

- (i) The service process is very difficult to measure accurately, as it is related to pushing man and machine to their limits;
- (ii) The outcomes of service processes are inherently more inconsistent in quality than for their manufacturing counterparts; and
- (iii) The risk factors in troubleshooting activities are always subjective and harder to control.

Madu (1999) discussed the development of a robust regression metamodel for a maintenance float policy, which originally referred to a technical crew problem. The factors affecting the system are divided into controllable variables of design factors and uncontrollable variables of noise factors. Madu (1999) extended the Taguchi method introduced by Kumar *et al.* (1996). Taguchi's orthogonal array was applied to the simulation experiment and *ANOVA* was used to analyse the simulation results. The best control factor was identified, and the relationships between the dependent variables and the best design for the production plant were explored. Madu (1999) developed metamodels from the regression analysis of significant factors and interactions. He assumed failure pattern to be in parametric linear form with regards to any censoring factors.

Yang and Chen (2000) measured the risk performance index, by using an explicit expression to compare the number of complaints that occurred with the desired target set by the firm. David and Xiao (2002) used an appropriate hypothetical project as the basis for a semi-structured questionnaire survey, for accruing the data required to allow robust statistical analyses to be applied. David and Xiao (2002) applied the *ANOVA* technique to compare service performance between countries. Statistical analysis of the troubleshooting time performances can help to improve the way maintenance is delivered to the customers. Conventional methods in statistics are widely used to measure the mean and standard deviation of repair time in different ways.

The statistical mean is always used as a measurement of central tendency of the density of a random variable, T . Then, the variability of T will be used to measure the dispersion of the density of T . The mean can be used to determine maintenance function effectiveness, while the standard deviation and variance give the variability of the measurements. For example, three separate repairing times, T_j , in hours for a specific type of machine, by technicians A and B are (1, 250, 10) and (79, 89, 93) respectively. Both technicians have the same mean repair time of 87 hours, while standard deviations for technicians A and B are 115 and 5.9 hours respectively. Thus, the mean does not express a spread dispersion of the density of troubleshooting time. Moreover, measures of repairing activities are subjective and intangible, and are always affected by the following factors:

- (i) Technicians are not sure when the best time for the parts to be replaced or repaired is;
- (ii) Technicians may not have enough resources for the job required; and
- (iii) Existence of organizational obstacles and risk factors.

Ellis *et al.* (1991) have used *MTTR* to analyse repair rates, which is:

$$\frac{1}{MTTR}$$

They estimated instantaneous *MTTR* prior to the analysis. Then, Boyer and Arnason (2002) used the mean value analysis to derive the utilization of staffs in repairing activities. They have used the single-class Markovian equivalent model of the multi-class, which is the memoryless model. They assumed service demand for repair as random as the Poisson process with time homogeneous arrival rates. As mentioned, *MTTR* does not express a spread dispersion of the density of repair time. Moreover, there was no concern about any risk factors that might be involved during a repairing time. Thus, in this study, we are introducing multiple criteria analyses for better estimates. Moubray (1997) highlighted some important points in maintenance:

- (i) Teamwork between maintenance crew and operators on the production floor;
- (ii) Decision support tools, such as reliability studies, failure modes and effects' analysis;
- (iii) When any failures occur, the ability to redesign the equipment with a much greater emphasis on reliability, or introducing backup and standby strategies; and
- (iv) Expert system development, such as automatic condition monitoring capabilities and remote maintenance management control.

Changes in the organizational environment have created a need for maintenance managers to concentrate on efficiency, environmental concerns and safety simultaneously. Water (2000) discussed three levels of departure points in maintenance quality management. Maintenance is defined as a control system by

using matrix representation. The columns of the matrix show the differentiation between structural and social aspects of the self-organizing layer, the adaptive layer, and the control layer. The rows of the matrix show the several levels of control. A better maintenance model for quality management can be formed, by handling both the rows and columns of the matrix respectively.

The matrix offers an opportunity to decide what maintenance is needed for quality management, and is used to decide what maintenance concepts are useful for each of its defined cells. Water (2000) proposed some structures for maintenance policy decision-making, *i.e.* practice use-based maintenance (*UBM*), condition-based maintenance (*CBM*) or failure-based maintenance (*FBM*), using qualitative matrix measure methodologies. The results provide top-level management justification for maintenance decision support in the respective functional group of the production lines.

2.6.13 Costing Analysis

Improved technology and the increased sophistication of maintenance personnel have led some companies to improve their reactive approach. Proactive strategies utilize preventive maintenance activities to prevent the failures from occurring at an early stage (Cui *et al.*, 2004). Gupta *et al.* (2001) developed analyses based on polling models, which could be used to obtain system performance metrics when preventive maintenance is conducted. They calculated the weighted sum of mean service waiting times to measure the overall preventive maintenance performance system. Some formulas are given by Gupta *et al.* (2001) to estimate preventive maintenance and manufacturing system performance. The preventive maintenance service is based on readings or measurements going beyond a predetermined limit. If a machine cannot hold a tolerance, other techniques, such as a *CBM* and *VBM*, are initiated. All this maintenance involves costs. Several attempts were made to analyse, predict and measure maintenance cost, as shown in Table 2.3.

Table 2.3: Costing Analysis in Maintenance

Researcher	Focus	Application	Approach
Thorstensen and Rasmussen (1999)	Costing analysis model in condition-based maintenance	Gas turbine costing in oil and gas productions	Stochastic measures
David and Kobbacy (2000)	Costing analysis in preventive maintenance	Simulation studies	Bayesian and Proportional hazards model
Frank (2000)	Costing analysis in failure-based maintenance	Simulation studies	Stochastic measures
Gabbar <i>et al.</i> (2003), Neves <i>et al.</i> (2004)	Cost estimation in reliability-centred maintenance, computerized maintenance management system and plant optimization	Simulation studies and model implementation in nuclear power plant	Stochastic and mathematical measures
Fujiyama <i>et al.</i> (2004)	Inspection cost in risk-based maintenance	Turbine plants	Reliability growth analysis
Al-Najjar and Imad (2004)	Cause elimination analysis in vibration-based maintenance	Paper company	Statistical analysis
Scarf <i>et al.</i> (2005)	Age-based replacement costing model for commuter railway system	Train traction motors	Statistical reliability measures
Al-Najjar (2007)	Evaluation on the financial impact in vibration-based maintenance	Mathematical formulation	Mathematical measures

Many researchers and practitioners are pursuing the development of various maintenance techniques to estimate the reliability of machineries, and embed them into *CMMS*. However, Labib (2004) found that the majority of commercial *CMMS* in the market are still lacking decision support for management. He has highlighted one of the reasons for this is that managers are unaware of the various types of maintenance optimization models. Another reason is that optimization models have:

- (i) Difficulty to collect raw data;
- (ii) Computational complexities;
- (iii) Complexity of modelling failure distribution; and

- (iv) Gap between theory and practice.

As mentioned, there is little assessment of the successful applications of the maintenance optimization model and they are still under-explored in *CMMS*. This motivates this research to give more choices to the programmers for plugging optimization procedures into *CMMS*. The study of the maintenance optimization procedures is given in the next section.

2.7 Maintenance Optimization

Optimization of maintenance is defined as an attempt to resolve the conflicts of a maintenance decision situation, in such a way that the variables under the control of the decision-maker take their best possible value (Jardine, 1973). One of the controllable variables in the case of machinery maintenance is the interval between failures and operation. The optimum value is achieved when the working area of the problem is satisfied. In broad terms, maintenance optimization consists of the maintenance techniques aimed at finding either the optimum balance between costs, time and benefits of maintenance, or the most appropriate moment to execute maintenance activities.

Production, quality, and maintenance are the three major concerns of any manufacturing firm (Chakraborty *et al.*, 2008). Optimization criterion in maintenance manufacturing is what maximizes the production profit and minimizes the total cost and time of the maintenance, as well as maintaining good quality work.

Rami and Vijaya (1996) suggested cost-optimal maintenance policies in terms of overhauls, with the assumption that each minimal repair will be completed within $0 < a < 1$ units of time and successive overhaul times constitute a non-decreasing geometric process. If N^* is the optimal number of overhauls, T^* is the optimal time, C_1 is a replacement cost and C_2 is a system overhaul cost per unit of time, then the resulting cost of the optimal repair (N^*, T^*) is:

$$\frac{C(N^* T^*)}{C_1} \text{ for some typical } \frac{C_1}{C_2},$$

using the optimal algorithm. From the formulae, Rami and Vijaya (1996) have shown that the optimal number of overhauls, N^* , increases and the resulting cost decreases, with an increase in the values of:

$$\frac{C_1}{C_2}$$

Also, the optimal time, T^* , increases and the resulting cost decreases, with an increase in the values of:

$$\frac{C_1}{C_2}$$

Harish *et al.* (2003) used different ways to integrate optimal design, production and maintenance planning into multipurpose plants. They wrote a computer program using the Mixed Integer Linear Programming (*MILP*) model. On the other hand, Pascual *et al.* (2008) presented a Mixed Integer non-Linear Programming (*MInLP*) model that minimized the expected overall cost of the repair. They used a mathematical formulation for the integrated optimal production and maintenance planning. Cornel *et al.* (2008) proposed competing risks models to identify the reliability and optimum indicators of the operation workers. They managed to categorize high risk and low risk in an optimistic graphical model, complete with their degree of dependence. If the maintenance is at a higher risk and the cost is expensive, then some outsourcing can be considered (Cornel *et al.*, 2008).

Another attempt made by Peter *et al.* (2005) was to simplify the outsourcing as a convex, minimum-cost, network flow problem. Then, they managed to solve it using the shortest path algorithm. The shortest path algorithm is the program used to find the length of a shortest path in the network between two vertices, in a connected, simple, undirected, weighted graph with n vertices (Rosen, 2007). These approaches are not practical in this study, as the accounting department of *SMI* is unable to release complete data on the maintenance costs due to confidentiality. Thus, further analysis on decision-making is difficult to publish.

2.7.1 Markovian Model

The Markovian optimization technique is a mathematical model, which is used to describe a stochastic process controlled by a sequence of actions. The machine is prone to random breakdowns and repairs. In maintenance, the system is also subjected to stochastic disturbances arising from accidents during repairs or other interventions. If a machine is operational, it may be producing or idle, or the machine may be locked out and shut down for periods of maintenance activities. In some cases, repairs are carried out without lock-out in situations where locking out is impossible. The modes of the machines in the production lines are given in Figure 2.10 (Charlot *et al.*, 2007).

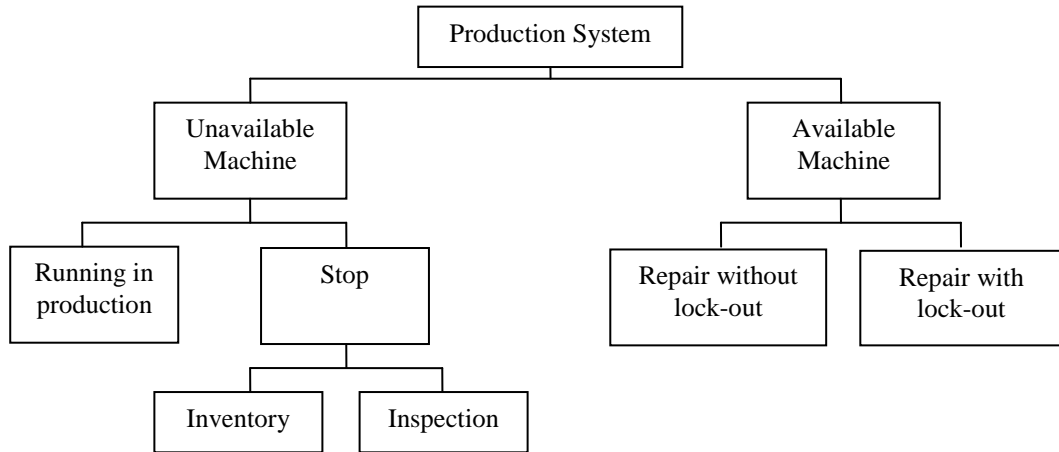


Figure 2.10: States of the Production System (Charlot *et al.*, 2007)

Based on Figure 2.10, the production system can be separated into discrete parts of the hybrid mode, *i.e.* $\zeta(t)$, $t > 0$, where it may experience different states at a particular time. For instance, let $M = \{1,2,3,4\}$, where M denotes the set of states or modes of the machine. Such a machine is available when it is operational ($\zeta(t) = 1$) and unavailable when it is under repair without lock-out ($\zeta(t) = 2$), lock-out for preventive maintenance ($\zeta(t) = 3$), and under repair where the machine is with lock-out ($\zeta(t) = 4$). The diagram in Figure 2.11 illustrates the transitions between different modes of the system.

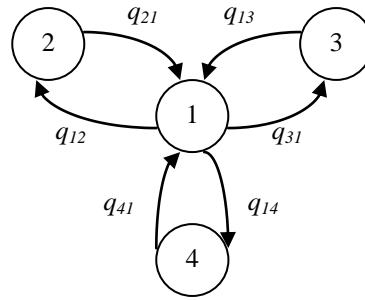


Figure 2.11: State Transition Diagram

This is the basic concept of the Markovian model, where a transition matrix is developed to estimate the parameters at particular transitions and absorbing states. Maintenance optimization is measured using the Markovian model, which is used aggressively by many practitioners, as shown in Table 2.4.

Table 2.4: Development of Markovian Model

Researcher	Focus	Parameter
Chiang and Yuan (2001)	Maintenance policy for periodic inspection	Repair time, replacement time, repair frequency
Chung and Chang (2002), Hsieh and Chiu (2002)	Determining the optimal number of standby components required in the system. Identify the optimal state in which the replacement of deteriorating components shall be made	Number of components, number of standby components, production time, idle time, profit
Adolfo and Antonio (2002)	Trade-off between flexibility and complexity of semi-Markovian probabilistic models	Failure rate, repair cost, repair time
Glazebrook <i>et al.</i> (2005)	General Markov decision process to call R number of repairmen to maintain a collection of M number of machines	Number of repairmen, number of machines

Abhijit (2006)	Risk sensitivity approach in the setting of renewal process in Total Productive Maintenance. Also solving risk-sensitivity analysis using Markov decision process	Failure time, repair cost, <i>PM</i> time
Charlot <i>et al.</i> (2007)	Realistic analysis model using Markovian analysis by considering machine age-dependent preventive and corrective maintenance policies on optimal stock levels	Stock level, machine age, maintenance cost
Dimitrakos and Kyriakidis (2008)	Constitution of deteriorating installation that transfers a raw material to a production unit and buffer, which may cause delays in production. Semi-Markov decision algorithm is developed to obtain optimal policies	Production machines, cost, buffer time, repair time, <i>PM</i> time

Needless to say, the Markovian model requires detailed observation of the previous and current states in order to predict the next state. But, in reality, from the maintenance case study in *SMI*, it is a big challenge to get a complete observation of machinery maintenance activities, especially when the problem escalates to the contractors. Since the data given is incomplete, we cannot design a complete state cycle diagram using the Markovian model for a given problem in our study.

2.7.2 Bayesian Model

The Bayesian model is a probabilistic graphical model for reasoning under uncertainty. It consists of a set of nodes or Vertices, with V representing random variables, a set of Links, L , connecting these nodes to form an acyclic directed graph, $G = (V, L)$, and P , a set of conditional probability distributions, $P(x)$. Here, x denotes a discrete random variable with n states of x_1, \dots, x_n . The nodes correspond one-to-one with the domain variables, such that there is one conditional probability distribution for each node given its parents in the directed graph. An acyclic, directed Graph, $G = (V, L)$, induces a set of conditional relations between the nodes of V . The set of relations of G changes when the states of a subset of the nodes of G are known

or observed events, called evidence. Evidence on the variables provides information on their states.

Conditional relations between nodes given from a set of evidence can be read from the directed graph, using linear complexity algorithms (Weidl *et al.*, 2005). If there is an arc from node A to another node B , A is called a parent of B , and B is a child of A . The set of parent nodes of node x_i is denoted by the parents (x_i). A directed acyclic graph is a Bayesian relative to a set of variables, if the joint distribution of the node values can be written as the product of the local distributions of each node and its parents as:

$$P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{parents}(x_i))$$

If node x_i has no parents, its local probability distribution is said to be unconditional, otherwise it is conditional.

Apeland and Scarf (2003) have provided a straightforward means of presenting uncertainty related to future events to decision-makers, by using the mixed method, subjective method and Bayesian method. Weidl *et al.* (2005) addressed key aspects of process conditional monitoring and root cause analysis. They have used the object-oriented Bayesian model to obtain some decision support for the complex continuous processes in maintenance.

As mentioned, the Bayesian model is appropriate when probabilistic and coefficient parameters are uncertain. In our case study, the variables, such as objectives, alternatives and criteria, are certain. Also, there is incomplete data on conditional relations to the problem in this research. Therefore, the model is reserved for our future study.

2.7.3 Simulation Model

Simulation is the imitation of some real thing, state of affairs, or process. The act of simulating something generally entails representing certain key characteristics or behaviours of a selected physical or abstract system. Simulation modelling is used to conduct analysis as a testing mechanism on maintenance applications. Simulation is always used because complete testing in a real situation is time-consuming and expensive. Nowadays, simulation is easy using computer software, such as Arena, ProModel, and BlockSim to estimate the risk factors. Hayek *et al.* (2005) reported that simulation is an effective optimization technique to model:

- (i) Machine breakdowns, delays, and bottlenecks;
- (ii) Estimated machine failure times, levels of damage, productivity losses and the required level of maintenance;
- (iii) Human resources, material availability, materials handling, and industrial processes;
- (iv) Engineering knowledge and experience; and
- (v) Costing, investment data associated with the above activities, and events.

Young and Yeol (2004) have used Monte Carlo simulation in order to decide on the optimal repair capacity, when both failures and repair times of individual host systems exhibit long-range dependent property. The term ‘Monte Carlo’ was coined in the 1940s by physicists working on nuclear weapon projects in the Los Alamos National Laboratory. The Monte Carlo method is a class of computational algorithms that rely on repeated random sampling to compute their results. The methods are often used when simulating physical and mathematical systems. Because of their reliance on repeated computation and random or pseudo-random numbers, Monte Carlo methods are most suited for simulation modelling using a computer. Using the Monte Carlo simulation, Young and Yeol (2004) obtained optimal capacity of maintenance based on utilization rate, average and maximum waiting times.

Kenne and Gharbi (2004) conducted simulation experiments, combined with experimental design, to estimate the optimal production and corrective maintenance policies. Hayek *et al.* (2005) used the simulation up-time of the machine or process as a series of critical modules. The model aided maintenance managers by creating a decision tool that optimized the life cycle maintenance cost of complex machinery in a short timeframe, by taking into account the routable nature of modules. Raid (2006) has shown a simulation-based parameter design approach for optimizing a machine operating strategy under stochastic running conditions. He collected data on the risk factors, including machine operating hours, operating pattern, scheduled shutdowns, maintenance levels, and product changeovers. Random factors included machine random variables of cycle time, *MTBF*, *MTTR* and defects rate. Machine performance, as a complicated function of control and random factors, is defined in terms of net productivity based on three key performance indicators, as follows:

- (i) Gross throughput;
- (ii) Reliability rate; and
- (iii) Quality rate.

Then, optimization complications results are obtained from the limited capability of mathematical modelling and experimental design in tackling the resulting large-in-space, combinatorial, optimization problem. Karin *et al.* (2007) presented a model to analyse the availability of k -out-of- N systems under block replacement, sharing limited spares and repair capacity. They have used computer technology to quantitatively simulate the relationship between control variables and system availability. In most cases, simulation is used when assuming a huge number of data or observations because manual calculation is time-consuming, while in terms of the case study in *SMI*, this assumption does not hold.

Today, the evolution of computers and information technology has led to the widespread use of artificial intelligence techniques in maintenance optimization, and is discussed in the following section.

2.7.4 Artificial Intelligence

In the past, decisions about maintenance policies are often carried out solely based on the experience of the maintenance crew. Besides, large amounts of available data are in manual forms. Thus, any kind of correlation cannot be used to facilitate the choice between reactive, preventive or predictive maintenance actions. Therefore, the result tends to be difficult to achieve and is scarcely optimized. In recent information technology development, all data is captured in the computer. Then, Artificial Intelligence (AI) techniques, such as neural networks, data mining and fuzzy logic, are used to merge with other maintenance techniques. The merged model is called a hybrid approach and is deployed widely in maintenance optimization (Jovelino and Sebastian, 2006).

AI models, such as neural networks, allow us to detect the underlying relationships among a large number of data. They make it possible to correctly pattern the failure of large sets of equipment, and to decide, for each of them, the correct maintenance strategies to be adopted. Bevilacqua *et al.* (2005) have proposed artificial neural networks to classify the same set of centrifugal pumps. They learned from historical data and captured functional relationships among the data, even if the underlying relationships are unknown or hard to describe. In doing so, it should be possible to reduce the necessity of the corrective maintenance activities and to simplify the planning of the preventive maintenance.

Angus *et al.* (2005) presented an approach to facilitate the allocation of labour resources in the aircraft maintenance industry. They have used a decision support system with the fuzzy sets. Jovelino and Sebastian (2006) extended the theory proposed by Angus *et al.* (2005) to build an expert system embedded with the concepts from fuzzy sets. They applied an expert system and fuzzy sets to automate the diagnosis analysis in power transformer industries. Combinations of mathematical, statistical and operational research with AI techniques are able to provide the hybrid approaches. The approaches may help to provide a useful decision support model to improve maintenance efficiency and effectiveness. The

mathematical models in this study can perhaps merge with *AI* as a hybrid approach in future research work.

2.7.5 Decision Support Model

The decision support model is built to help the maintenance operation team in their job to choose the best next executable action (Christine and Alain, 2003). The decision will use the scheduling done by those responsible for production to establish the priority of the products in the unit. Afterwards, the model will establish and update the ordered list of executable actions for each maintenance category and suggest the next task to execute (Christine and Alain, 2003). There are several ways in which a decision support analysis can be applied in maintenance optimization. Dekker and Scarf (1998) explained a few ways in which to conduct an analysis for decision support:

- (i) A case study;
- (ii) A strategic decision support system; and
- (iii) An operational decision support system.

In a case study, specific problems, for which a dedicated model is built, are studied, analysed and executed. The strategic decision support system is used each time for one-off problems at a high level in systems or units. The only difference now is that a comprehensive model is already available in a *DSS* at the start of the problem. Whereas the operational *DSS* is a system developed for a repetitive problem, like the planning and scheduling of maintenance for some production lines.

Pascual and Ortega (2006) have proposed a novel model to determine optimal life-cycle duration and intervals between overhauls, by minimizing global maintenance costs. They have used the integration by parts to make a decision on whether equipment should be repaired, overhauled or replaced during preventive maintenance.

Liao *et al.* (2008) integrated maintenance and production programs with the economic production quantity model for an imperfect process, involving a deteriorating production system with an increasing hazard rate: imperfect repair and rework upon failure. They used some mathematical formulas on calculating costs for preventive maintenance and provided decisions on the optimum run time, which minimizes the total cost. Note that one of the most crucial problems in many decision support models is the precise evaluation of data. Very often, in real-life decision-making applications, data are imprecise and fuzzy (Sasmal and Ramanjaneyulu, 2007). The research work is limited to investigate decision-making options in *FBM*. Hence, it is desirable to obtain certain important criteria before deriving some decision-making procedures, as is discussed in the next section.

2.7.6 Multiple Criteria Decision-Making Model

One of the most common problems in many engineering and business applications is how to evaluate a set of alternatives in terms of a set of decision criteria (Shyjith *et al.*, 2008). For example, let someone intends to set up computer servers. There are a number of different configurations available to choose from. The different operating systems are the alternatives. Here, a decision should also consider cost and performance characteristics, such as processing unit speed, memory capacity, network bandwidth, number of clients, *etc.* Alternatives of software, maintenance, expendability should be considered too. These may be some of the decision criteria for this case, where the criteria may vary based on different purpose of the servers. The Multiple Criteria Decision-Making (*MCDM*) model is the problem-solving model, and can be used to determine the best alternative for the above example.

The model consists of a finite set of alternatives, which decision-makers have to select or rank to a finite set of criteria, weighted according to their importance. Then, the model is structured to M alternatives and N decision criteria. Each alternative can be evaluated in terms of the decision criteria. After that, the relative

importance or weight of each criterion can be estimated as well. Let a_{ij} , where $i = 1, 2, 3, \dots, M$ and $j = 1, 2, 3, \dots, N$ denote the performance value of the i th alternative in terms of the j th criterion. Also, let W_j denote the weight of the criterion C_j . Then, Genova *et al.* (2004) gave the core of the typical *MCDM* as represented in the formula in matrix (2.1).

Alternative	Criterion				
	$C_1 W_1$	$C_2 W_2$	$C_3 W_3$...	$C_N W_N$
A_1	a_{11}	a_{12}	a_{13}	...	a_{1N}
A_2	a_{21}	a_{22}	a_{23}	...	a_{2N}
A_3	a_{31}	a_{32}	a_{33}	...	a_{3N}
.
.
.
A_M	a_{M1}	a_{M2}	a_{M3}	...	a_{MN}

(2.1)

The decision matrix is constructed, complete with the priority rating of each alternative with respect to each criterion, using a suitable measure. The evaluation ratings are then aggregated, taking into account the weights of the criteria, to get a global evaluation for each alternative and a total ranking of the alternatives. Given the above decision matrix, the decision problem considered in this study is how to determine which is the best alternative with the N decision criteria combined. For instance, if the decision problem is to select the best project to be funded, one is only interested in identifying the best candidate project. In another case, if it is to allocate the budget among a number of competing projects, one may be interested in identifying the relative importance of each project, so that the budget can be distributed proportionally to the significance of each project.

In a simple *MCDM* situation, all the criteria are expressed in terms of the same unit, such as Malaysian Ringgit, hours, metres, *etc.* However, in many real-life *MCDM* problems, different criteria may be expressed in different units. Examples of such units include pound figures, political impact, regional impact, *etc.* These multiple dimensions make an *MCDM* problem a complex one. That is why research

in *MCDM* is numerous, diverse, and found in many applications, as is shown by the examples given in Table 2.5.

Table 2.5: Research on *MCDM* Model

Researcher	Focus	Application	Approach
Labib (1998a), Fernandez <i>et al.</i> (2003)	<ul style="list-style-type: none"> Design, development and implementation of <i>CMMS</i> with criteria analysis and decision mapping Customized features on maintenance maturity grid and decision analysis 	Automotive sector	<ul style="list-style-type: none"> Mathematical formulas <i>DMG</i>
Karsak (2000)	<ul style="list-style-type: none"> Development of procedure and algorithm to evaluate alternatives in flexible manufacturing system 	Mathematical analysis and simulation	<ul style="list-style-type: none"> <i>MCDM</i> algorithm with fuzzy data
Al-Najjar and Imad (2003), Labib (2004)	<ul style="list-style-type: none"> Development of hybrid intelligent approaches Systematic analysis of the system with combination on multiple criteria analysis and fuzzy rule-based techniques 	Mathematical calculation and simulation using Fuzzy logic	<ul style="list-style-type: none"> <i>DMG</i> Multiple criteria decision analysis Fuzzy logic rules
Kaklauskas <i>et al.</i> (2005)	<ul style="list-style-type: none"> Solution to perform a multivariate design and multiple criteria analysis of alternate alternatives based on the enormous amount of information Development of multivariate design method and multiple criteria for a building refurbishment's analysis 	Public building of Vilnius Gediminas Technical University	<ul style="list-style-type: none"> Decision making matrix Weightage analysis
Ana <i>et al.</i> (2007), Anish <i>et al.</i> (2008)	<ul style="list-style-type: none"> Optimization framework on optimal maintenance planning Arrangement of maintenance schedules for PM by considering few criteria: availability, maintenance cost, life cycle costs and tolerance level 	Paper production, nuclear production plant	<ul style="list-style-type: none"> Multiple-objective Genetic algorithm <i>MATLAB</i> toolbox

Villanueva <i>et al.</i> (2008)	<ul style="list-style-type: none"> Survey result to show the applicability of an approach based on a combination of distribution-free tolerance interval and genetic algorithms for testing, and maintenance optimization of safety-related systems 	Simulation using Monte Carlo and genetic algorithm	<ul style="list-style-type: none"> Multiple-objective genetic algorithm
------------------------------------	--	--	--

Labib (2004) revealed that the Decision-Making Grid (*DMG*) is the most suitable model for continuous improvement in *MCDM*. This is because when machines in the top ten list of worst performers have been appropriately dealt with, then others will move down in the list and resources can be directed at these new offenders. If this practice is continued, then all machines will eventually be running optimally. In another attempt, Ramiro (2002) concluded that *AHP* is the only model in *MCDM* that is able to conduct pairwise comparisons of attractiveness and use default measurement scales. Similar comments were given by Sasmal and Ramanjaneyulu (2007), who explained why *AHP* is the most famous *MCDM* technique in their study. The sensitivity of criteria weights in *MCDM* can be evaluated from a holistic approach with *DMG* and *AHP*, as described in the next section.

2.7.7 Decision-Making Grid

There are many researchers who have studied the Decision-Making Grid (*DMG*) and apply it in the equipment management area. Among those, there are three selected reviews that are worth discussing under this sub-section. In the first, Labib (1998a) has introduced the *DMG* model to help maintenance management identify breakdown maintenance strategies. In short, *DMG* is a control chart in two-dimensional matrix forms. The columns of the matrix show the three criteria of the downtime, whilst the rows of the matrix show another three criteria of the frequency of the failures. The model consists of these three steps:

- (i) Criteria analysis;
- (ii) Decision mapping; and
- (iii) Decision support.

Here, a better maintenance model for quality management can be formed by handling both the rows and columns of the matrix respectively. The matrix offers an opportunity to decide what maintenance strategies are needed for decision-making, such as to practice *OTF*, *FTM*, *SLU*, *CBM*, *DOM*.

The second important review was undertaken by Fernandez *et al.* (2003), in which implementation of *DMG* in *CMMS* was discussed in detail. They extended the theory of the maintenance maturity grid and implemented it into a disk brake pad manufacturing company in England. The results can provide maintenance policies in the respective functional group in production lines, to achieve their common goal to reduce downtime. Later, Labib (2004), in the third review, comprehended the model and demonstrated the hybrid intelligent approach using the *DMG* and fuzzy rule-based techniques. In this study, the *DMG* is employed in small and medium food processing companies to identify maintenance strategies, and more detail is available in the following chapters.

DMG is used in this study as the model is flexible, and considers *OTF*, *FTM*, *SLU*, *CBM*, *DOM*, *TPM* and *RCM* strategies in the same grid. The model is able to analyze multiple criteria and is the best choice when the number of machines is less than fifty (Pascual *et al.*, 2009). It can be used to detect the top ten problematic machines on the production floor with several system conditions. This is with regards to failures such as fatigue, imbalance, misalignment, loosened assemblies, and turbulence, which can occur in rotational or reciprocating parts such as bearings, gearboxes, shafts, pumps, motors and engines. Identifying the top ten problematic machines is in alignment with the 80-20 rule. The rule states that eighty percent of the problems arise from the same twenty percent of the root causes. In another word, once twenty percent of the root cause had been fixed, then eighty percent of the problem is resolved. The application of the model can have a breakthrough performance, as it fulfils the purpose of the model to map machines into a certain grid in a matrix and suggests the appropriate maintenance strategies to comply with.

2.7.8 Analytical Hierarchical Process

The Analytical Hierarchical Process (*AHP*) is a robust and powerful multi-criteria decision-making tool for complex problems, where both qualitative and quantitative aspects are considered (Davidson and Ashraf, 2003). By fitting this model to data, the impact on the selection of alternatives can be obtained. This gives guidelines to adjust the existence of certain alternatives, which will be the milestones by which to improve maintenance operations. The *AHP* is introduced by Saaty (1980) to help analysts to organize the critical aspects of a problem into a hierarchical structure, similar to a family tree. By reducing complex decisions in the tree to a series of simplified rankings from grandparent to grandchild nodes, *AHP* provides a clear rationale for the choices made. Later, Saaty (1994) extended his study and built *AHP* with a more concrete concept of valuable observation, that the hierarchical approach to problem-solving is that the functional representation of a system may differ from person to person, but people tend to agree on the bottom level of alternative actions to be taken and the level above it. Now, let us consider the first step in *AHP*: the decomposition of the problem into a decision hierarchy, as shown in Figure 2.12 (Vassou *et al.*, 2006).

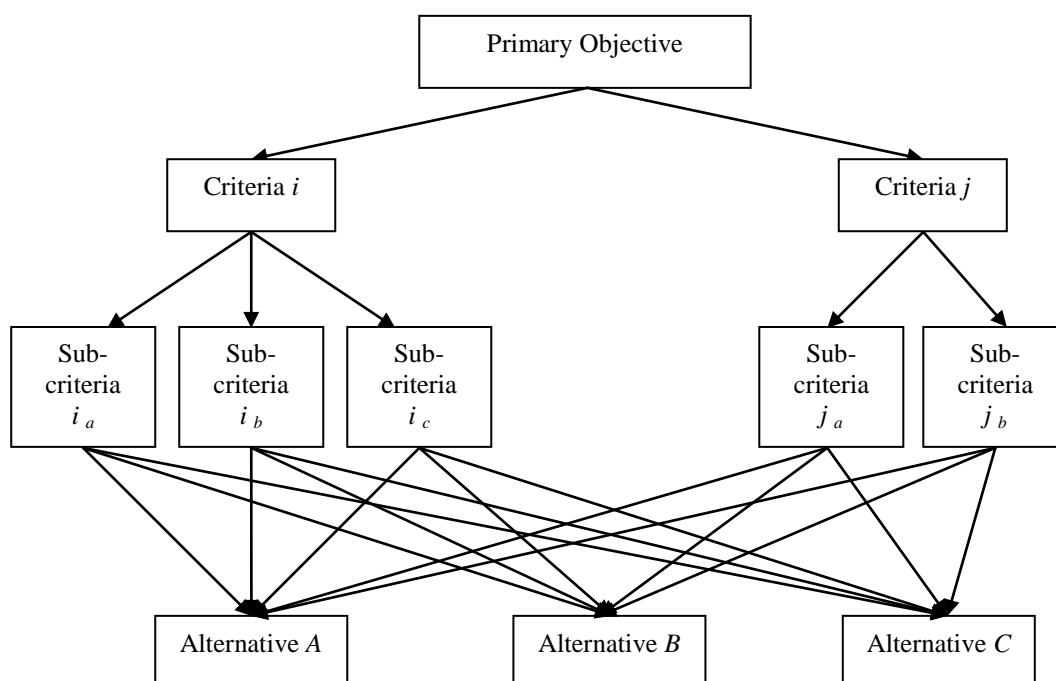


Figure 2.12: *AHP* Decision Hierarchy (Vassou *et al.*, 2006)

Next, the following step is used to establish priorities among the elements in the hierarchy, by making pairwise comparisons of the criteria and alternatives of all factors in their respective levels. Given Criterion i and Criterion j , these comparisons are carried out using a predefined one-to-nine ratio scale given by Wind and Saaty (1980). The next step is the calculation of a list of the relative weights of the criteria, based on their *eigen* values and *eigen* vectors. Then, the maintenance engineers are able to rank choices in order of their effectiveness in meeting conflicting objectives or priorities.

Clearly, the *AHP* is most efficiently applied when the total number of criteria and alternatives is not excessive (Vassou *et al.*, 2006). Bertolini *et al.* (2004) commented that the elements appear to be logically constructed in a hierarchy as a by-product of the entire *AHP* approach. In other words, *AHP* is not only a problem-solving technique, but also a modelling tool of the problem concerned. The tool supports decision-makers in choosing between the alternatives. It helps to quantitatively estimate how well the alternatives fulfil a number of performance requirements, which themselves can be either quantitative or qualitative (Marjan *et al.*, 2005).

AHP has been applied extensively in many areas, including the following (Williams, 2005):

- (i) Evaluating employees in terms of their worth to a company;
- (ii) Rating potential recruits;
- (iii) Assessing tenders to a procurement requirement;
- (iv) Selecting management policies to attain objectives;
- (v) Selecting between candidate companies for a merger or acquisition;
- (vi) Evaluating the quality of software products;
- (vii) Selecting the future role for a prison;
- (viii) Prioritizing hazardous wastes to determine a schedule for cleanup;
- (ix) Selecting a location for a new hospital; and
- (x) Rating potential projects in terms of their contribution to strategic objectives.

From the above applications, there is still little assessment of *AHP* in the maintenance optimization model, and the applications in *FBM* are still under-explored. Some applications of *AHP* in the maintenance area are given in Table 2.6.

Table 2.6: Application of *AHP* in Maintenance

Researcher	Focus of the study	Tools
Labib (1998a), Labib and Shah (2001), Grewal <i>et al.</i> (2008)	<ul style="list-style-type: none"> • Systematic decision process combined with <i>MCDM</i> for strategic decision-making • Development of generic framework on consistency and sensitivity analysis for a continuous improvement process 	<ul style="list-style-type: none"> • Logistic approach • Sensitivity analysis using Expert Choice software
Ashraf <i>et al.</i> (1998), Yasin (2009)	<ul style="list-style-type: none"> • Identifying the criteria upon which engineering personnel wish to formulate a maintenance decision or action • Rank different criteria according to criticality by an in-depth detailed graphical and hierarchical format 	<ul style="list-style-type: none"> • Mathematical calculation • Graphical tools
Bevilacqua and Braglia (2000), Bettolini and Bevilacqua (2006), Wang <i>et al.</i> (2007)	<ul style="list-style-type: none"> • Selecting best maintenance strategy for Italian oil refinery and thermal power plant in China • Identify the best strategy from five alternatives: preventive, predictive, condition-based, corrective and opportunistic maintenance 	<ul style="list-style-type: none"> • Qualitative study • Goal programming • Fuzzy prioritization methods
Reza and Ashraf (2003)	<ul style="list-style-type: none"> • Structure the decision-making process for the selection of a manufacturing system among feasible alternatives, based on the reconfigurable manufacturing study 	<ul style="list-style-type: none"> • Gradient analysis • Expert Choice software
Davidson and Ashraf (2003)	<ul style="list-style-type: none"> • A systematic and generic methodology for the implementation of design improvements based on experience of past failures • Illustrate the implementation in the form of a case study by identifying the changes made to Concorde before the accident. The flight crashed after take-off from France, causing the death of 113 people 	<ul style="list-style-type: none"> • Qualitative analysis by investigation of Concorde flight, <i>AFR 4590</i> after the accident on July 25th, 2000

Ali and William (2004)	<ul style="list-style-type: none"> • Systematic model for evaluating different maintenance organizational structures with respect to the objectives of a maintenance department • The result provides step-by-step guidelines for the maintenance management and decision makers 	<ul style="list-style-type: none"> • Quantitative analysis on four given alternatives for the maintenance system in a steel company
Carnero (2005), Carnero (2006), Chauhan <i>et al.</i> (2008)	<ul style="list-style-type: none"> • Decision-making in relation to the selection of the diagnostic techniques and instrumentation in the predictive maintenance programs • Significant analysis related to quality, safety, availability and cost reduction in industrial plants 	<ul style="list-style-type: none"> • Factor analysis • Decision rules • Lubricant analysis • Vibration analysis
Abdul Hamid <i>et al.</i> (1999), John (2005), Vassou <i>et al.</i> (2006), Percin (2006)	<ul style="list-style-type: none"> • Best alternative selection process 	<ul style="list-style-type: none"> • Questionnaires • Spreadsheets • Sensitivity measures in a matrix form • Goal programming

In the past, Reza and Ashraf (2003) discovered that there are not many researchers who have used *AHP* model for strategic decision-making in manufacturing lines, even the model is very powerful. Moreover, the *AHP* approach has been effective for selecting next-generation manufacturing paradigms based on environmental, product, technology and social factors (Alvi and Labib, 2001). Therefore, in this study, *AHP* is employed as a multi-criterion, strategic, justification approach for breakdown maintenance analysis in small and medium food processing industries. More detail is provided in Chapter 6.

2.8 Conclusion

Maintenance is a logistic interrelated function to support production processes, so their efficiencies are difficult to appreciate in absolute terms. Here, maintenance policies vary among specific functional groups within the same organization. Maintenance management personnel need to analyse the type of maintenance policies and strategies to be implemented at the right time, and this clearly depends on each item of equipment. In brief, this chapter provides a review on general maintenance concepts, policies, optimization, information system and their techniques. The area of maintenance optimization has tremendous potential for investigation, as more researchers and practitioners are becoming interested in achieving maximum production output with minimum cost. Therefore, serious effort is put into this research to review and discuss available maintenance techniques, their recent development, and their applications in maintenance optimization.

As mentioned previously, there is little assessment of the successful applications of the maintenance optimization model and it is still under-explored. This motivates us to provide a brief insight into the optimization techniques used to aid maintenance decision-making, such as the Markovian model, Bayesian model, *DSS*, *AI* techniques, and *MCDM*. At the end of the chapter, *DMG* and *AHP* models have been reviewed. *DMG* is a powerful model, as it is able to detect the top ten problematic machines on the production floor in two-dimensional matrices. Then, the maintenance strategies to comply with are recommended by the model. The *AHP* model is interesting as it is able to integrate both quantitative and qualitative techniques. Application of the *DMG* and *AHP* models can provide breakthrough performance, as they are able to calculate the lower boundary and upper boundary of all alternatives. They are also able to provide a clear comparison between the alternatives and will be discussed in the next chapters.